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DESIGN AND EVALUATION OF THE HUMAN-BIOMETRIC SENSOR INTERACTION METHOD

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DESIGN AND EVALUATION OF THE HUMAN-BIOMETRIC SENSOR INTERACTION METHOD

A Dissertation

Submitted to the Faculty

of

Purdue University

by

Eric P. Kukula

In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

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Purdue University

West Lafayette, Indiana

I dedicate this dissertation to my family and close friends who have given me support and encouragement throughout this journey.

I would like to especially dedicate this…

to my mother for her love, patience, understanding, and support – it means more than you will ever know;

to my step father for his understanding, encouragement, and support;

to my father who looks down from above for always motivating me and who instilled in me at a young age the importance of education, and that anything is possible, as long as you work hard and put your mind to it.

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I am also very grateful for having an exceptional doctoral committee and would like to thank Dr. Niaz Latif, Dr. Vincent Duffy, and Dr. Mathias Sutton for their support, collaboration, and encouragement.

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I am also extremely grateful to Michael Chaudoin of Upek, Incorporated for providing the fingerprint sensors and data collection software used in this research. Without Mike's support for investigating the HBSI, the PUSH sensor would not have been possible. Further, I would like to thank Upek's engineers working with Mike to get the prototype software complete for capturing fingerprint images from the "push"-based fingerprint swipe sensor.

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LIST OF ABBREVIATIONS

Organizations

ANSI	American National Standards Institute
BSPA	Purdue University Biometric Standards, Performance, and Assurance Laboratory
DHS	Department of Homeland Security
FBI	Federal Bureau of Investigation
IBG	International Biometric Group
IEA	International Ergonomics Association
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IRB	Institutional Review Board
ISO	International Organization for Standardization
NASA	National Aeronautics and Space Administration
NCR	National Cash Register
NIST	National Institute of Standards and Technology
NRC	National Research Council
NSF	National Science Foundation
UK	United Kingdom
UKPS	United Kingdom Passport Service
US	United States
US-VISIT	United States Visitor and Immigrant Status Indicator Technology

General

ANOVA	Analysis of Variance
CAM	Computer Aided Manufacturing
CFR	Code of Federal Regulations
CNC	Computer Numerical Control
HBSI	Human-Biometric Sensor Interaction
HCI	Human-Computer Interaction
JTC	Joint Technical Committee
MGL	Michael Golden Laboratory
NISTIR	NIST Internal Report
SC	Sub Committee
SD	Standing Document
SOC	Standard Occupational Classification

TR	Technical Report

Biometric Performance

DET	Detection Error Tradeoff
EER	Equal Error Rate
FAR	False Acceptance Rate
FMNR	False Non-Match Rate
FMR	False Match Rate
FRR	False Rejection Rate
FTA	Failure to Acquire
FTE	Failure to Enroll
ROC	Receiver Operating Characteristic

Biometric Related

AFIS	Automated Fingerprint Identification System
CCD	Charge Coupled Device
CMOS	Complementary Metal Oxide Semiconductor
DPI	Dots per inch
DRAM	Dynamic Random Access Memory
IAFIS	Integrated Automatic Fingerprint Identification System
FTIR	Frustrated Total Internal Reflection
LED	Light Emitting Diode
NBIS	NIST Biometric Image Software
NFIQ	NIST Fingerprint Image Quality
PDA	Personal Data Assistant
RF	Radio Frequency
USB	Universal Serial Bus
UV	Ultra Violet
WSQ	Wavelet Scalar Quantization

Data Collection / Biometric Sensors

LA	Large Area commercial capacitance fingerprint sensor
PULL	Fabricated swipe-fingerprint form factor which users pull towards the body to use
PUSH	Fabricated swipe-fingerprint form factor which users push away from the body to use
UPEK	Commercial swipe-fingerprint form factor

Ergonomics / Usability

CTS	Carpal Tunnel Syndrome
GOMS	Goals, Operators, Methods, and Selection rules
MSD	Musculoskeletal Disorder
UCD	User Centered Design
UEM	Usability Evaluation Method

ABSTRACT

Kukula, Eric, P., Ph.D., Purdue University, August, 2008. Design and Evaluation of the Human-Biometric Sensor Interaction Method. Major Professor: Stephen J. Elliott.

This research investigates the development and testing of the Human-Biometric Sensor Interaction Evaluation Method that used ergonomics, usability, and image quality criteria as explanatory variables of overall biometric system performance to evaluate swipe-based fingerprint recognition devices. The HBSI method was proposed because of questions regarding the thoroughness of traditional testing and performance evaluation metrics such as FTA, FTE, FAR, and FRR used in standardized evaluation methods; questioning if traditional metrics were acceptable enough to fully test and understand biometric systems, or determine if important data were not being collected.

The Design and Evaluation of the Human-Biometric Sensor Interaction Method had four objectives: (a) analyze the literature to determine what influences the interaction of humans and biometric devices, (b) develop a conceptual model based on previous research, (c) design two alternative swipe fingerprint sensors, and (d) to compare how people interact with the commercial and designed swipe fingerprint sensors, to examine if changing the form factor

improves the usability of the device in terms of the proposed HBSI evaluation method.

Data was collected from 85 individuals over 3 visits that accounted for 33,394 interactions with the 4 sensors used. The HBSI Evaluation Method provided additional detail about how users interact with the devices collecting data on: image quality, number of detected minutiae, fingerprint image size, fingerprint image contrast, user satisfaction, task time, task completeness, user effort, number of assists; in addition to traditional biometric testing and reporting metrics of: acquisition failures (FTA), enrollment failures (FTE), and matching performance (FAR and FRR).

Results from the HBSI Evaluation Method revealed that traditional biometric evaluations that focus on system-reported metrics are not providing sufficient reporting details. For example, matching performance for right and left index finger reported a FRR under 1% for all sensors at the operational point 0.1% FAR: UPEK (0.24%), PUSH (0.98%), PULL (0.36%), and large area (0.34%). However, the FTA rate was 11.28% and accounted for 3,768 presentations. From this research, two metrics previously unaccounted for and contained in the traditional FTA rate: Failure to Present (FTP) and False Failure to Present (FFTP) were created to better understand human interaction with biometric sensors and attribute errors accordingly. The FTP rate accounted for 1,187 of the 3,768 (31.5%) of interactions traditionally labeled as FTAs. The FFTP was much smaller at 0.35%, but can provide researchers further insight to help explain abnormal behaviors in matching rates, ROC and DET curves. In addition, traditional metrics of image quality and number of detected minutiae did not reveal a statistical difference across the sensors, however HBSI metrics of fingerprint image size and contrast did reveal a statistical difference, indicating the design of the PUSH sensor provided images of less gray level variation, while the PULL sensor provided images of larger pixel consistency during some of the data collection visits. The level of learning or habituation was also documented in this research through three metrics: task completion, Maximum User Effort (MUE), and the number of assists provided. All three reported the PUSH with the lowest rates, but improved the most over the visits, which was a function of learning how to use a “push”-based swipe sensor, as opposed to the “pull” swipe type.

Overall the HBSI Evaluation Method provided the foundation for the future of biometric evaluations as it linked system feedback from erroneous interactions to the human-sensor interaction that caused the failure. This linkage will enable system developers and researchers the ability to re-examine the data to see if the errors are the result of the algorithm or human interaction that can be solved with revised training techniques, design modifications, or other adjustments in the future.

CHAPTER 1. INTRODUCTION

1.1. Objectives

The goal of this research was to provide the biometrics community with a comparative evaluation method for a swipe-based fingerprint recognition device that uses ergonomics, usability, and image quality criteria as explanatory variables of performance of the independent variable – form factor design. There were four objectives:

1. Analyze literature in the fields of: biometrics, ergonomics, Human-Computer Interaction (HCI), and usability in order to determine what influences the interaction between the human and the biometric device and what aspects of ergonomics, Human-Computer Interaction (HCI), and usability can be applied to the design of biometric devices, specifically a swipe-based fingerprint device.
2. Develop a conceptual model for the design of biometric devices in general.
3. Create two alternative swipe-based fingerprint form factors based on the conceptual model developed in (2) that includes concepts from biomechanics and anthropometry of the hand and fingers, biometrics, and the qualitative data results from the interviews to gather personal

perceptions and common interaction problems for swipe-based fingerprint recognition devices.

4. Evaluate the commercially available and new form factor devices, created in (3), in a comparative performance evaluation using the proposed Human-Biometric System Interaction (HBSI) evaluation method, which was discussed in (2).

This study manipulated the form factor of the fingerprint sensor. The form factor, typically a plastic composite or metal material, is the material surrounding the electrical components and circuitry, shown in Figure 1. The fingerprint sensor was the same across all three swipe-based devices, meaning the capacitance chip that was used in the commercial device and two form factors designed in this study were the same model.

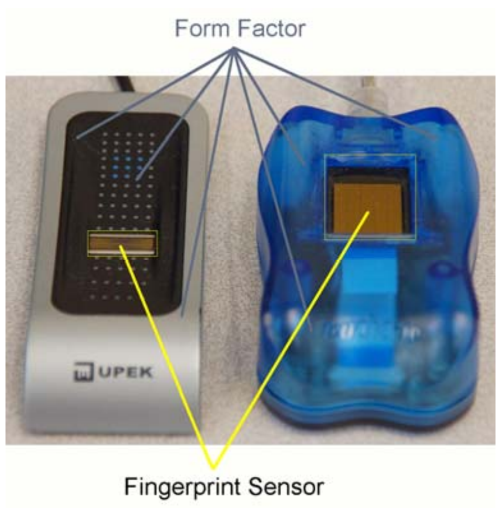


Figure 1 Fingerprint sensor and form factor diagram for the commercial swipe-based sensor (left) and large area sensor (right).

1.2. Organization

This dissertation covers numerous aspects concerning the proposed Human-Biometric Sensor Interaction evaluation method. This dissertation covers five chapters: the introduction, review of literature, methodology, results, and the conclusions and recommendations.

1.3. General Introduction

The term biometrics has two distinct meanings. Biometrics, or biometry, has been commonly used since the early twentieth century to describe a field that develops statistical and mathematical methods for data analysis problems in the biological sciences (International Biometric Society, 2006). The other meaning, developed during the early 1970s to describe emerging technologies that use physical and behavioral traits of humans, which are defined by the International Organization for Standardization (2007) as the automated recognition of behavioral and physiological characteristics of individuals. This research involves the latter definition.

Biometric technologies are used to authenticate individuals in a multitude of applications; they may be stand-alone systems or utilized as part of a multi-factor authentication system (i.e., combined with physical possessions, such as an identification card, or knowledge, such as a personal identification number). Biometric technologies are typically discussed as belonging to one of two different types, namely behavioral and biological (also sometimes referred to as physiological). Behavioral biometrics include signature and voice recognition;

biological or physiological biometrics include face, finger, hand geometry, and iris recognition. Some modalities overlap these two categories, as they are functions of both behavioral and biological characteristics; for example, voice, face, and signature have components that are dependent upon each other.

1.4. Statement of the Problem

While personal identification techniques using physical and behavioral characteristics date back to almost 3000 B.C., it was not until the middle of the twentieth century that academics developed automated techniques, which is the differentiating factor between other identification techniques and biometrics as it is currently defined. However, it was not until the 1970s that the first commercially available biometric systems emerged. Since biometrics entered the commercial marketplace, most research has been dedicated to the development in three areas: improving performance, increasing throughput, and decreasing the size of the sensor or hardware device. Moreover, limited research has focused on usability and issues relating to how users interact and use biometric devices, thus user interaction errors have been coded and analyzed as system errors. But as biometric performance evaluations continue to grow in complexity and standardized testing protocols and technical reports emerge such as ISO 19795-1(2006a), ISO 19795-2 (2007a), and ISO TR19795-3 (2007b), many physical, behavioral, and social factors can now be attributed to degradation of biometric system performance. Thus, if we can attribute these factors to the user and not the sensing technology or algorithm, it must be examined in order to continue improving the overall biometric system.

Looking at fingerprint recognition, one can see the importance of investigating how users interact with different biometric devices. Fingerprint recognition is the most widely used of the biometric technologies, with popular applications in law enforcement (e.g., the Integrated Automatic Fingerprint Identification System — IAFIS), access control, time and attendance, and personal computer/network access. The current biometrics industry report published by the International Biometric Group (2006) states that fingerprint recognition holds approximately 44% of the biometric market. Traditionally, the high market share has been due to law enforcement applications, but over the last two years, the list of applications for fingerprint technologies has grown tremendously due to sensors evolving at a rapid pace and to a wider spread of applications. Applications for fingerprint recognition have expanded from law enforcement and computer desktop single sign-on applications to personal data assistants (PDA), mobile phones, laptop computers, desktop keyboards, mice, and universal serial bus (USB) flash media drives, to name a few. In particular, the growth of one fingerprint vendor (in terms of volume) reached new highs last fiscal year — shipping one million sensors between 1998-2003, four million between 2003-2005, and five million sensors in 2006 (Burke, 2006). This broadening of markets can be explained by the following – as devices get smaller, cost decreases, as less material is required, thus the number of potential applications increases. This statement is supported by the increase in revenue, as well as market projections, which are shown in Figure 2.

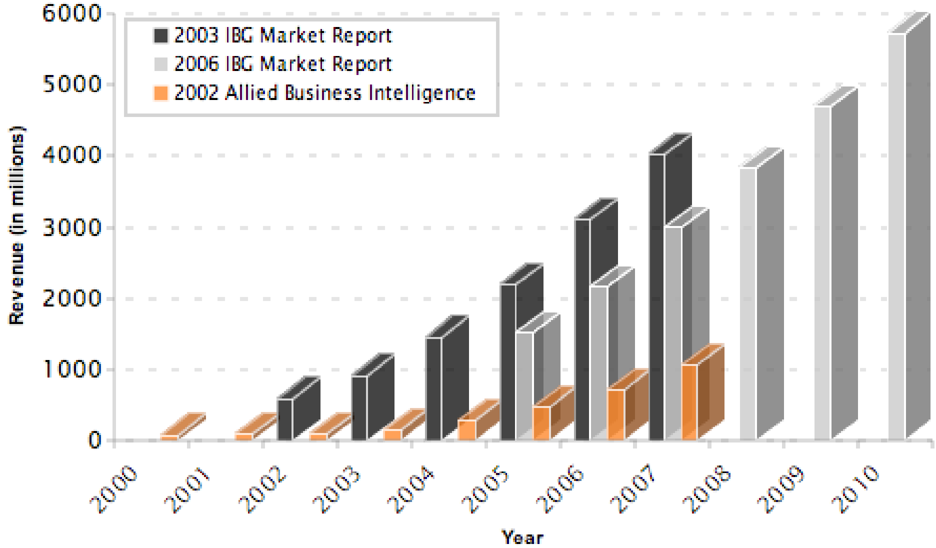


Figure 2 Industry reports of real and projected biometric revenue (Allied Business Intelligence, 2002; International Biometric Group, 2002, , 2006).

The successful deployment of biometric systems, regardless of modality or application, needs to take into consideration how individuals interact with the device. Failure to do so may cause a degradation of the optimal performance of the biometric sensor, causing problems such as: Failure to Acquire, Failure to Enroll, and impact on the False Rejection Rate. And if an individual cannot successfully interact with a biometric device, there is a potential for failure to use, especially if they have had previous negative experiences with a biometric sensor.

Therefore the use of biometrics will likely be dependent on individuals' ability to not only use it more *effectively*, but also find it more *useful* than the technology that it replaces (such as the username / password combination in a computer sign-on application), and *like* it, which are the components of usability as outlined in ISO 9241-11 (1998). Therefore, as utilization of biometric technology becomes more pervasive, understanding the interaction between the human and the biometric sensor becomes imperative and must be investigated. This research attempts to gain a better understanding of how users interact with swipe-based fingerprint devices by taking into account the following:

- Biomechanics and anthropometry of the hand and fingers,
- Individual perceptions and issues related to biometric devices, and
- Common interaction problems between the human and device.

By taking into account the bulleted list above in the design of a swipe-based fingerprint form factor, it may be possible to reduce one or more of the following:

- Failure to Acquire (FTA) rate,
- Failure to Enroll (FTE) rate,
- Number of placement/interaction errors, and
- Amount of task/movement time.

The preceding items are measured in the proposed HBSI evaluation method because if a reduction in amount of assistance (training), errors, or time is achieved, it may be possible to increase overall user satisfaction, which is also measured separately in the HBSI method.

1.5. Significance of the Problem

While biometric sensors and the supporting technologies have advanced over the last five years; driven by improved sensor technology, improved data storage and compression capabilities, and improved computing power, there has been limited research and literature that examines the design or usability of biometric devices even though the literature has discussed the need for work in this area. The following five items discuss the significance for this research.

1.5.1. 2003 Biometric Research Agenda: Report of the NSF Workshop

In 2003, over fifty-five leading biometric experts met under the sponsorship of the National Science Foundation (Grant EIA-0240689) to "develop a rational and practical description of crucial scholarly research to support the development of biometric systems" (Rood & Jain, 2003, p. 3). Even though the focus of much research has been on improving mathematical performance, the group did recognize ergonomics and usability. Moreover, the proposed research agenda did contain an item stating the need for research on ergonomic design of the capture system and usability studies to evaluate what the effects are on biometric system performance (Rood & Jain, 2003).

1.5.2. Biometrics: A Grand Challenge

Literature in biometrics has recognized that ergonomics and usability may affect the performance of the system but have not provided results to further quantify this. In *Biometrics: A Grand Challenge*, co-authors Jain, Pankanti, Prabhakar, Hong, and Ross (2004) state that the complexity of designing a biometric system is based on three main attributes – accuracy, scale (size of the database), and usability, which is illustrated in Figure 3. Jain et al. (2004) discuss that many applications only require a biometric system to operate at one of the three extremes and the real challenge is to design a system that operates at the extreme of all three axes. However, in the next section which frames the rest of the paper, Jain et al. (2004) “categorize the fundamental barriers in biometrics into four main categories (i) accuracy, (ii) scale, (iii) security, and (iv) privacy” (p. 937). Note, usability is not included in this statement, but was one of three supporting legs to the characterization proposed in the paper.

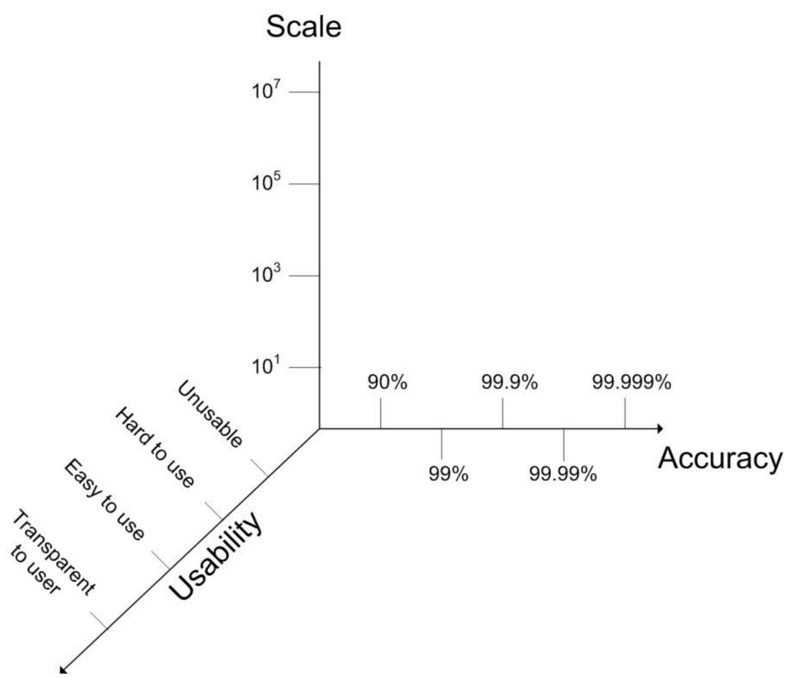


Figure 3 Biometric system characterization with axis representing the intrinsic 1:1 accuracy of the matcher (Jain, Pankanti, Prabhakar, Hong, & Ross, 2004).

1.5.3. UK Passport Service Biometrics Enrollment Trial

In 2004, the United Kingdom Passport Service (UKPS) along with other government agencies and consultant Atos Origin implemented a trial contributing towards a national identity cards scheme that investigated the test processes, customer experience, and attitudes during enrollment and verification of face, iris and fingerprint biometric systems (Atos Origin, 2005). The report discusses exception cases that include physical and mental impairments, process times, as well as an assessment of customer perceptions and reactions to the systems. While the report discusses multiple issues regarding the usability of biometric systems, the following three points indicate the need for continued research regarding the human-system interaction. First, the enrollment rates for the disabled, which combined both learning and physical impairments, were much lower than the UK “representative” group. Second, users fifty-five and older found it much more difficult to position themselves to interact with the fingerprint device than the 18-34 and 35-54 age groups. Lastly, the report recommends that “further trials are needed specifically targeted towards those disabled groups where enrollment difficulties occurred because of environment design or because of the ergonomics of the biometric device design” (Atos Origin, 2005, p. 15).

1.5.4. 2005 National Research Council Workshop on Technology, Policy, and Cultural Dimensions of Biometric Systems

On March 15-16, 2005, members from government, industry, and academia met to discuss and present their views on issues involving biometric technologies and systems. In the first of five sessions participants discussed “the state of the art of biometric systems, the current bottlenecks, and areas where performance could be improved” (Batch, Millett, & Pato, 2006, p. 2). The panelists agreed that “biometric systems cannot be made perfect – that is, the focus should be on how to evaluate and reduce, rather than eliminate, error rates” (Batch, Millett, & Pato, 2006, p. 2). Moreover, they grouped the challenges on biometric systems into three groups:

- Improving accuracy through research on sensor resolution, ergonomics, algorithms, fusion techniques, etc…,
- Integrating biometric systems with other security systems, and
- Promoting interoperability of biometric systems (Batch, Millett, & Pato, 2006, p. 2).

Furthermore, the report states the “capture of biometric identifiers by the sensors is affected by both the human interaction with the sensor and by the precision of the acquisition device itself” and “given that users of biometric systems may not be familiar with the technology, the ergonomics of the sensor and associated data capture hardware may affect the biometric information that is collected” (Batch, Millett, & Pato, 2006, p. 6).

1.5.5. National Institute of Standards and Technology Internal Report 7382

The most recent work regarding usability or ergonomics outside of Purdue’s Biometric Standards, Performance, and Assurance Laboratory has been conducted by the National Institute of Standards and Technology (NIST). At the time of writing, the NIST biometrics usability group has published three reports on the usability of biometric devices, one conference proceeding article, and one document that outlines a taxonomy of usability and biometric definitions. One of these reports, NISTIR 7382 (2006) investigates if the height of a fingerprint sensor has an effect on fingerprint image quality for the Department of Homeland Security in accordance with section 303 of the Border Security Act, codified as 8 U.S.C. 1732. The study attempted to answer three questions:

1. Does work surface height affect the time required to capture fingerprint images?
2. Does work surface height affect the quality of captured fingerprints?
3. Do users prefer a particular work surface height for capturing fingerprints (Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006)?

Results from the study, which the setup is shown in Figure 4, consisted of seventy-five NIST employees using a fingerprint scanner that was six inches tall revealed significantly different results for each of the three questions. The height of 36 inches (914 mm) resulted in fastest performance, a second height – 26 inches (660 mm) produced the best quality fingerprint images, and yet users found a third counter height of 32 or 36 inches (813 or 914 mm) to be most comfortable (Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006). In addition, starting the fingerprint capture with the right hand for the slap based prints was most efficient as 76% of the participants preferred starting with the right hand, which is in line with traditional handedness statistics of 11-13% being left handed.

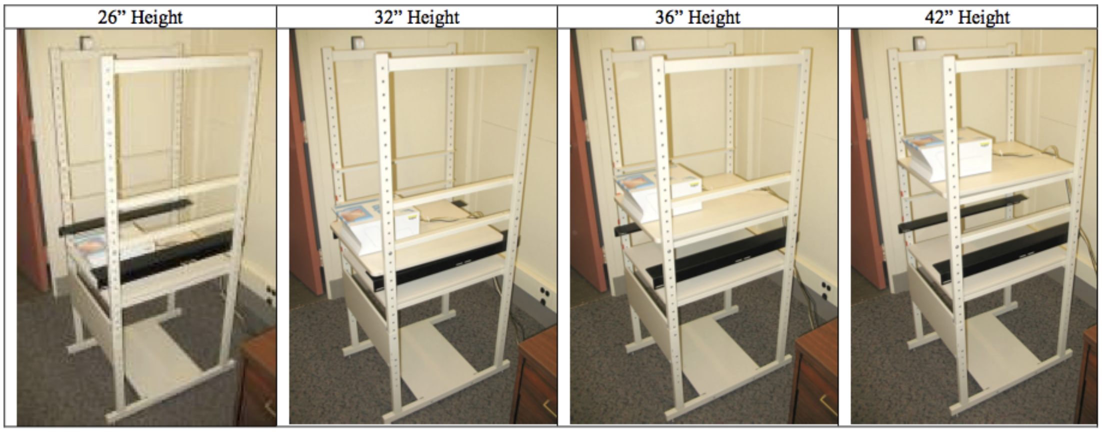


Figure 4 Test apparatus showing the four scanner height adjustments (Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006).

1.6. Statement of Purpose

The purpose of this study was to develop two alternative swipe-based fingerprint form factors using a commercially available fingerprint sensor based upon the biomechanics and anthropometry of the hand and fingers, ergonomic principles, common interaction problems, and errors users perform, as well as user perceptions. The comparative study evaluated the performance and usability of the two form factors created in this study, the commercially available swipe-based fingerprint form factor, and one large-area fingerprint sensor. The study used participants from Purdue University and the Greater Lafayette area. The test was conducted on Purdue University's West Lafayette campus in the Biometric Standards, Performance, and Assurance (BSPA) Laboratory located in

Knoy Hall room 378. The BSPA laboratory was also used for the qualitative data collection to during times when the lab was minimally occupied to minimize distractions and auxiliary input on individuals participating in the interviews.

1.7. Definition of Terms

Terms and definitions are used throughout this dissertation that may be unfamiliar to the reader. Most definitions are included in context of the document, however the terminology that is unfamiliar to the biometrics community is included in this section.

Anthropometry - empirical science that evaluates body measurements; such as size, strength, shape, mobility, flexibility, and working capacity, as well as defines physical dimensions and characteristics of a person such as: weights (masses), volumes, centers of gravity, and body segments (Bhattacharya & McGlothlin, 1996; Pheasant, 2006; Tayyari & Smith, 2003).

Dactyloscopy - Forensic identification science that is associated with ridges on the finger tip areas only (Ashbaugh, 1991).

Ergonomics - scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data and methods to design in order to optimize human

		well-being and overall system performance (International Ergonomics Association (IEA), 2006).
Form factor	-	material in which a biometric sensor is embedded in.
Human-Computer Interaction	-	discipline concerned with the design, evaluation and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them (Hewett et al., 1996).
Usability	-	extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use (International Standards Organization, 2006b).

1.8. Assumptions

1. The swipe-based fingerprint capacitance sensor functioned consistent with the manufacturer’s specifications, regardless of the form factor.
2. The designed composite material that the form factor was constructed with did not affect the availability of the swipe-based fingerprint capacitance sensor.
3. The pseudo-random ordering of the fingerprint devices mitigated habituation effects to one sensor over another for the tested population.

4. The pseudo-random ordering of the fingerprint devices mitigated personal preferences and user satisfaction over the three visits for the tested population.
5. The composite material of the designed fingerprint devices versus the material of the commercial fingerprint devices did not affect the personal preference and user satisfaction for the tested population.

1.9. Delimitations

1. Testing of fingerprint technologies other than capacitance was outside the scope of this study.
2. Testing of large or small area fingerprint sensors was outside the scope of this study. Although, one large area sensor is included in the study to collect a baseline measure that can be used to evaluate the three swipe-based sensors.
3. Testing of fingerprint sensors embedded in devices such as cell phones, PDAs, laptops, etc… was outside the scope of the study.
4. Testing of various swipe based fingerprint capacitance sensors was outside the scope of this study.
5. Testing of algorithms was outside the scope of this study.
6. The HBSI conceptual model was designed for general biometrics, but the evaluation method was designed for only physical interactive biometrics. Testing of non-physical interactive biometrics was outside the scope of the evaluation method, and thus this study.

7. Testing was limited to the following classification shown in Table 1.

Table 1 Evaluation Classification (Mansfield & Wayman, 2002).

Experimental Application Types	Classification for this research
Application Classification	Scenario
Co-operative or Non Co-operative	Co-operative Users
Overt versus Covert	Overt
Habituated versus Non-Habituated	Both
Attended versus Non-Attended	Attended
Standard Environment	Yes
Public versus Private	N/A
Open versus Closed System	Closed

8. Spoofing of the swipe fingerprint sensor and housing was outside the scope of this study.
9. The methodology and protocol used ISO 19795-1(2006a), ISO 19795-2 (2007a), and ISO 25062 (2006b) as a guide, but deviations occurred due to the nature of the study. Please refer to the Chapter 3.
10. Aware WSQ Image Quality software and NFIQ were used, but were not compared.

CHAPTER 2. REVIEW OF LITERATURE

2.1. Introduction

The following review of literature is composed of eight sections. The first section discusses the history of personal identification, the history of biometrics, and foundations of fingerprinting. The second section discusses the Integumetary system, specifically the structure of the skin, ridge formations, and fingerprint patterns. The third section discusses the different fingerprint acquisition technologies and algorithms. The fourth section discusses the uniqueness of fingerprints, the size of the sensor, and finger selection and usage. The fifth section discusses the biometric model and typical characteristics found in a biometric system. This section will explore issues and problems satisfying these criteria and properties and reveal problematic areas in the human-biometric sensor interaction (HBSI). Here the business drivers for investigating this problem will be discussed. Section six will introduce anthropometry, ergonomics, usability, and user-centered design to show how using these tools could solve some of the issues discussed in section five. The seventh links the tools in section six and introduces the Human Biometric Sensor Interaction (HBSI) conceptual model. The last section introduces the proposed HBSI evaluation method, relating hypotheses, and an explanation of the statistical analyses that were used.

2.2. History of Personal Identification and Origins of Biometrics

The notion of utilizing personal information, characteristics, or human physiology for identification purposes is not a new concept. Throughout human history, man was often identified with his family, tribe, or clan through visual characteristics such as, but not limited to, clothing and personal artifacts, tattoos, or caste marks (Allison, 1973). Ancient Egyptian civilizations dating back to the fourth dynasty (circa 2575-2465 B.C.) used demographic information, behavioral characteristics, and anatomical measurements to identify individuals and ensure proper and fair distribution of food and supplies to workers. Ashbourn (2000) discuses the story of Khasekem, an assistant, who was responsible for administering and controlling food and supplies to Egyptian construction workers for King Chephren during which time The Great Sphinx and second pyramid in Giza were built. During his post, Khasekem became increasingly wary of fraudulent claims by workers attempting to claim their monthly food and supply allowance and sought to develop a system to better identify individuals. Khasekem’s system included the worker’s name, age, place of origin, and occupation, as well as unique physical and behavioral characteristics (Ashbourn, 2000). According to Ashbourn (2000) anatomical measurements supplemented the individual’s record if few distinctive features were apparent, which included “the distance between the tip of an outstretched thumb and the elbow” (p. 2).

2.3. History of Fingerprinting

Fingerprints have been found during excavations in ancient civilizations dating as far back as 7000 B.C. on bricks in the ancient city of Jericho and in the walls of the ancient city of Paphos (Kenyon, 1970; Maier & Karageorghis, 1984). Over the years fingerprints have also been found on everyday utensils and pottery, but according to Berry and Stoney (2001) the earliest trace of finger imprints left with intent occurred in Mesopotamia circa 3,000 B.C. to verify construction work of buildings for the king were built by respected masons. The Babylonians also understood that no two hands were exactly alike and used imprints of the hand to authenticate engravings and types of artwork for kings (Ashbourn, 2000). Berry and Stoney (2001) also infer that the Chinese were "aware of the individuality of fingerprints well over 5000 years ago" (p. 13). This inference is based on a left thumbprint embedded in the seal of an ancient Chinese script dated before 300 B.C., which is similar to the Chinese land contract shown in Figure 5. Berry and Stoney (2001) quoted Mr. Laufer, a researcher at the Field Museum of Natural History in the United States, about the Chinese's use of fingerprints stating "before the first century B.C., clay seals were used extensively in sealing documents such as official letters and packages" and that this left thumbprint is "deep and sunk into the surface of the clay seal and beyond any doubt was effected with intentional energy and determination" and "belongs to the owner of the seal who has made his name on the reverse side" (p. 13). According to Mr. Laufer, this thumbprint is the oldest manuscript on record documenting the history of the fingerprint system (Berry &

Stoney, 2001). In addition to fingerprints, the Chinese recognized the uniqueness of palm and foot prints (Allison, 1973). The novel *The Story of the River*, by twelfth century author Shi-naingan discusses the use of children’s sole and palm prints for completing transactions, for which the children were sold. The earliest reference linking fingerprinting to criminals dates back to Babylon during the reign of Hammurabi, circa 1792-1750 B.C. (Ashbaugh, 1991).

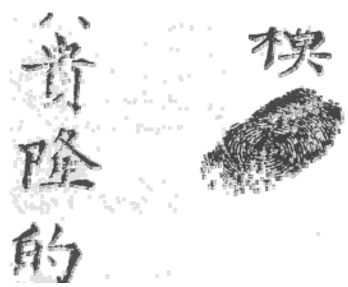


Figure 5 A Chinese land contract with thumbprint (Ashbaugh, 1991).

Moving ahead in time, ambassadors and foreign merchants around Persia during the fourteenth century had their fingerprints taken upon arrival for identification purposes. Rashid, a Persian physician, discusses his work with fingerprints in *Cyclopaedic History* which states that in Rashid’s experience “no two individuals have fingers precisely alike” (Morland, 1950).

2.3.1. Scientific Research in Fingerprints

2.3.1.1. <u>Nehemiah Grew</u>

While various applications and uses of fingerprints were used as far back as 3,000 B.C., the scientific research into fingerprints did not occur until the seventeenth century. Dr. Nehemiah Grew, M.D., an English botanist, physician, and microscopist published a paper in 1684 describing fingerprints as ridges, furrows, and pores in *Philosophical Transactions* (Allison, 1973; Ashbaugh, 1991; Block, 1969). Specifically, Grew (1684) described fingerprints as:

> Those great *Lines* to which some men have given Names, and those of a middle size call'd [called] the Grain of the skin innumerable *little Ridges,* of equal bigness and distance, and everywhere running parallel one with another. And especially, upon the ends and first Joynts [joints] of the *Fingers* and *Thumb*, upon the top of the *Ball*, and near the root of the *Thumb* a little above the *Wrist*. In all which places they are regularly disposed in to *Spherical Triangles*, and *Ellipticks*… Upon these *Ridges* stand the *Pores*, all in even *Rows*and of the magnitude, as to be visible to a very good Eye without a *Glass [magnifying glass]*…. That which Nature intends in the position of these *Ridges,* is, That they may the better suit with the use and motion of the Hand: those of the lower side of every *Triangle*, to the bending in or clutching of the Fingers: and those of the other two sides, and one of the Ellipticks to the

> pressure of the Hand or Fingers ends against any body, requiring them to the right and left. Upon these *Ridges*, the *Pores* are very providently placed, and not in the *Furrows* which lie between them; that so their structure might be more sturdy, and less liable to be depraved by compression; whereby only the *Furrows* are dilated or contracted, the *Ridges* constantly maintaining themselves, and so the *Pores* unalter'd [unaltered] (pp. 566-567).

In addition to Grew's detailed descriptions of the ridges and pores, Grew provided illustrations of the fingers and palm, as well as ridge and pore detail, which are depicted in Figure 6. However, Grew did not discuss the uniqueness of fingerprints or even consider it as a viable way for personal identification (Ashbaugh, 1991).

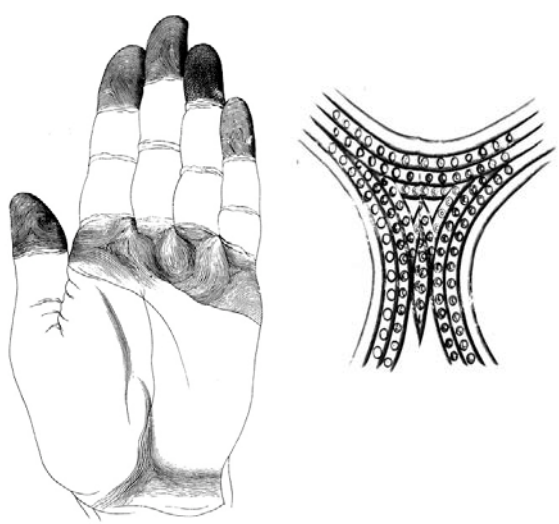


Figure 6 Illustrations by Grew in 1684 displaying the ridge flow of the fingers and palm [left] and a partial thumbprint depicting ridge detail and pores [right] (Grew, 1684).

2.3.1.2. Govard Bidloo

Studies concerning friction ridges were also ongoing in Holland around the same time as Grew published his research. In 1685, Govard Bidloo published a book on human anatomy titled *Anatomica Humani Corporis* that illustrated friction ridges and the structure of the pore (Allison, 1973; Ashbaugh, 1991). It is also of interest that Bidloo, like Grew, did not discuss individuality or uniqueness of fingerprints. Bidloo's illustration of a thumbprint can be seen in Figure 7.

Figure 7 Bidloo's illustration of a thumbprint exaggerating the friction ridges (Ashbaugh, 1991).

2.3.1.3. Marcello Malipighi

Marcello Malipighi, an Italian doctor and anatomy professor at the University of Bologna, made many contributions to science. The one of importance to this research is Malipighi's seminal research in a field called microscopic anatomy. It is believed that Grew and Malipighi were in correspondence, but the language barrier proved difficult to continue collaboration. Malipighi's contribution to the fingerprinting community surrounded his research that examined the functions of the human skin, specifically the lower epidermis, which is named the "Malipighian layer". Specifically, Malipighi discussed the function of the friction ridges for enhancing grasping objects (Ashbaugh, 1991; Berry & Stoney, 2001; Block, 1969).

2.3.1.4. <u>J.C.A. Mayer</u>

The next major contribution to the fingerprinting community took another century to emerge. In 1788, a German doctor and anatomist named Mayer published *Anatomische Kupfertafeln nebst dazu gehörigen Erklörungen*, which illustrates friction skin, and is depicted in Figure 8. More impressive than Mayer's illustrations are the comments concerning friction ridges and individuality:

> Although the arrangements of skin ridges is never duplicated in two persons, nevertheless the similarities are closer among some individuals. In others the differences are marked, yet in spite of their peculiarities of arrangement all have a certain likeness.

According to Ashbaugh (1991) this was the foundation of friction ridge identification, which is based upon two principles: fingerprints can be classified and ridge formation is random thus duplication never occurs.

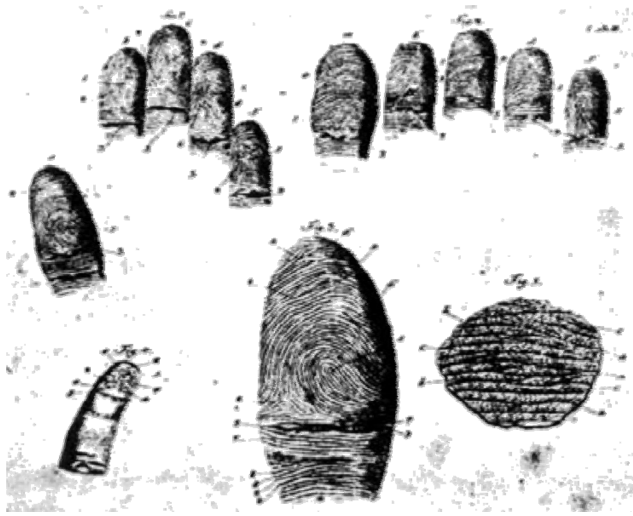


Figure 8 Mayer's illustration of fingerprints (Ashbaugh, 1991).

2.3.1.5. Thomas Bewick

While Mayer is believed to have been the first to scientifically disseminate knowledge on the uniqueness of fingerprints, Thomas Bewick deserves notice as he utilized engravings of his fingerprints for his signature, which is shown in Figure 9. While it can be deduced that Bewick thought ridge detail was unique, scholars are unsure how he determined this (Berry & Stoney, 2001; Block, 1969).

Figure 9 Thomas Bewick's signature including fingerprint (Berry & Stoney, 2001).

2.3.1.6. Joannes E. Purkinje

Continuing the discussion on classification, Joannes Evanelista Purkinje, a Professor of Anatomy at the University of Breslau in Prussia, published a thesis titled *Commentatio de examine physiologico organi visus et systematis cutanei* in 1823 that discussed research concerning the eye, fingerprints, and other skin features. Focusing on the fingerprint research, Purkinje was studying sweat glands and realized the sweat glands opened out into the furrows or grooves of the skin and observed the ridge patterns appeared to be unique for the individuals he studied (Ashbourn, 2000). More importantly, Purkinje listed nine classes or types of fingerprints (Figure 10), which was the first attempt at a classification system (Allison, 1973; Ashbaugh, 1991; Berry & Stoney, 2001; Block, 1969; Cummins & Wright-Kennedy, 1940). Purkinje's classification system of nine types is shown in Table 2. However, like those before him, Purkinje never states that the observed 'individual differences' in fingerprints, the palm, or hair might be useful in the recognition of individuals (Cummins & Wright-Kennedy, 1940). Purkinje also made many observations concerning the integumentary system, which includes the skin, hair, and nails. Purkinje's observations during tactual examinations classified skin as: "hard or soft, moist, oily, clammy, or dry, warm or cold, elastic, rigid, or spongy, smooth or rough, loose or taut, pliant or non-pliant" (Cummins & Wright-Kennedy, 1940). Moreover Purkinje stated that furrows become 'occluded in advanced age', which is one of the first statements discussing the wearing of friction ridges (Cummins & Wright-Kennedy, 1940).

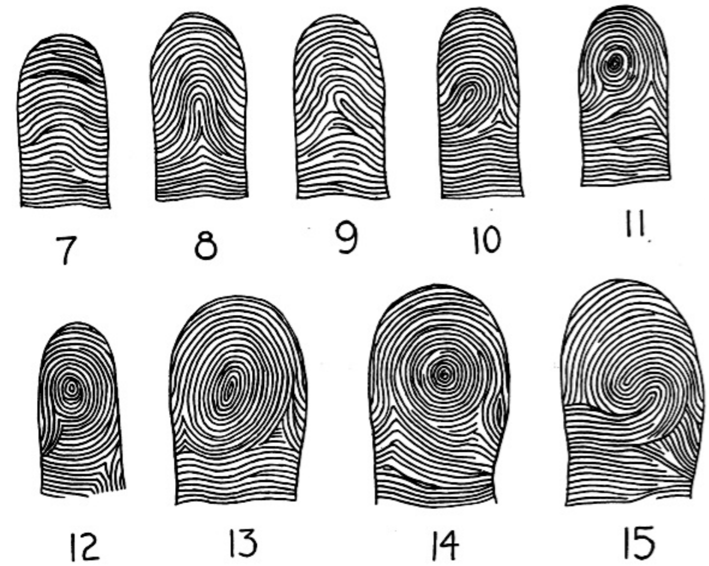


Figure 10 Purkinje's fingerprint classification patterns (Cummins & Wright-Kennedy, 1940).

Table 2 Purkinje's classification system with descriptions.

Pattern shown in Figure 10	Purkinje's Classification	Known today as:	Purkinje's description (Cummins & Wright-Kennedy, 1940):
7	Transverse curves	Plain arch	The ridges and furrows are almost in straight lines transversely from one side to the other except in the middle where they become more curved.
8	Central longitudinal stria	Tented arch	Similar to the transverse curve except the ridges are wrapped over a little perpendicular stria [column of ridges].
9	Oblique stripe	Radial or ulnar loop	Between the transverse curves an oblique line is interpolated from one side to the other and runs distally and ends almost in the center.
10	Oblique loop	Radial or ulnar loop	Similar to the oblique stripe except the curve returns to the side from which it came.
11	Almond	Whorl	A loop that runs back on itself enclosing an almond-shape gyrus and composed of concentric ridges.
12	Spiral	Whorl	Similar to the almond but the curves change from straight lines to loops suddenly and typically bear to one side.
13	Elliptical	Whorl	Similar to the other whorls, but the ridges form concentric ellipses that surround a simple short line placed in the center.
14	Circle	Whorl	Similar to the elliptical, except the simple line is replaced with a tubercle [island].
15	Double whorl	Double whorl	Two whorls are formed entwined on themselves.

2.3.1.7. Who Came First: Dr. Henry Faulds or Sir William Herschel?

Controversy has plagued the next two fingerprint pioneers and their findings therefore will be discussed in the order in which their publications in *Nature* appeared.

2.3.1.7.1. Dr. Henry Faulds

The first publication regarding the practical use of fingerprints and their use to identify criminals was published by Dr. Henry Faulds, a Scottish physician working at the Tsukiji Hospital in Japan as a surgeon, in *Nature* in October of 1880. In Faulds's letter "On the Skin-furrows of the Hand", he describes his research on monkey fingerprints and their similarities to the human. However, the most important part of Faulds's letter described five uses of finger patterns:

1. We may perhaps be able to extend to other animals the analogies found by me to exist in the monkeys.
2. These analogies may admit of further analysis, and may assist, when better understood in ethnological classifications.
3. If so, those which are found in ancient pottery may become of immense historical importance.
4. The fingers of mummies, by special preparation, may yield results for comparison. I am very doubtful of this.
5. When bloody finger-marks or impressions on clay, glass, & c., [etc…] exist, they may lead to the scientific identification of criminals (p. 605).

Faulds also conducted research on the permanence of friction ridges, as did Herschel, amongst others. These experiments will be discussed in section 2.5.8.

2.3.1.7.2. Sir William Herschel

In response to Faulds, Sir William Herschel published in *Nature* a month later in November 1880. In his letter, “Skin Furrows of the Hand” Herschel discussed his usage of fingerprints in applications such as identifying prisoners and for pensioners in India twenty years before Faulds (Herschel, 1880). Also, according to Block (1969) by 1860 Herschel became convinced that “the fingerprints of no two people were exactly alike – not even those of identical twins” (pp. 4-5).

Upon hearing word of Herschel’s work Faulds wrote a letter to the British Home Secretary in Scotland Yard claiming priority in his discovery of fingerprints, but his request was ignored (Block, 1969). Pressing the issue, Faulds sent a letter to Charles Darwin on February 15, 1880 requesting aid to gather finger impressions to ‘throw light on human ancestry’ (Berry & Stoney, 2001). Darwin replied that he could not offer assistance, but would forward Faulds’s letter to his cousin, who would later become Sir Francis Galton.

2.3.1.8. Sir Francis Galton

While the letter was passed onto Galton, it did not obtain the attention of him and was deposited into the Anthropological Institute where it stayed until 1894 (Berry & Stoney, 2001). During this time Galton was considered an expert in Bertillonage, a measurement system of the body that will be discussed in section 2.7.1. However, in 1888 Galton became very interested in fingerprints, first only with thumb impressions, then in 1890 moved to collect full sets of impressions, and after extensive study became convinced that fingerprints remained unchanged throughout life (Berry & Stoney, 2001; Block, 1969). Galton also proposed a system of classification that reduced Purkinje's classification system of nine types to three common classes: the arch, loop, and whorl, which is shown in Figure 11 (Allison, 1973). Galton also described minute details in fingerprints, called minutiae points and commonly called "Galton features", which are shown in Figure 12.

Figure 11 The five common fingerprint classes.

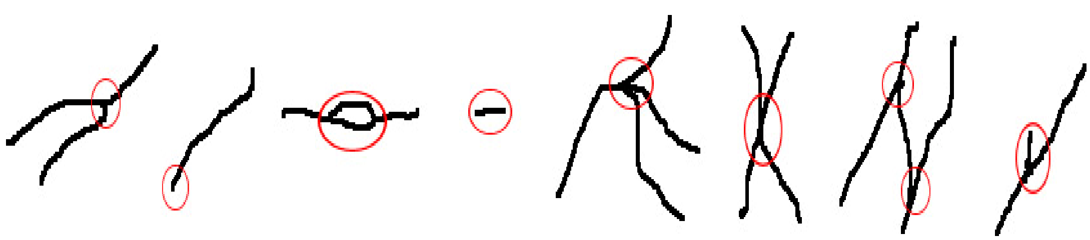


Figure 12 Minutiae structures Galton identified in fingerprints. From left to right: bifurcation, ridge ending, enclosure, island, trifurcation, crossover, bridge, and hook.

It is also reported by Galton (1892) in *Finger Prints* that:

> I [Galton] was exceedingly obliged to him [William Herschel] for much valuable information when first commencing this study, and have been almost wholly indebted to his kindness for the materials used in this book for proving the persistence of the lineations throughout life (p. 27).

Galton also states in *Finger Prints* that “if the use of finger prints ever becomes of general importance, Sir William Herschel must be regarded as the first who devised a feasible method for regular use, and afterwards officially adopted it” (Galton, 1892, pp. 28-29). As already mentioned, Galton was an expert in Bertillonage prior to his work in fingerprints. After only five years working in fingerprints Galton was summoned by the Home Secretary appointed Asquinth Committee to inquire into:

> (1) the existing methods of registering and identifying habitual criminals in England; (2) the Bertillon system of anthropometric criminal identification; and (3) the suggested system of identification by means of a record of fingermarks, and to report whether either of such (2) and (3) methods could with advantage be adopted either in substitution for or to supplement the existing records (Morland, 1950, p. 30).

The committee decided to add Galton's fingerprint classification to the Bertillon cards and it remained that way until the turn of the twentieth century (Morland, 1950).

2.3.1.9. Sir Edward Henry

The other name typically mentioned in the same breath as Galton is Sir Edward Henry. Henry followed Herschel in India, utilizing fingerprints for payroll and pension systems to insure that the proper person was being paid (Allison, 1973; Berry & Stoney, 2001). Controversy has surrounded the Henry Classification System in the past, as according to Berry and Stoney (2001) Henry gave his name to the system worked out by Indian co-workers Khan Bahadur Azizul Haque and Rai Bahadur Hem Chandra Bose, which Haque allegedly stated that Henry could not understand the system when it was patiently explained to him. In 1926, Henry addressed Haque stating that Haque contributed more than any other on Henry's staff (Berry & Stoney, 2001).

2.4. Fingerprint Classification Systems

2.4.1. Henry System

Henry's system further developed Galton's ideas and classified fingerprints by categorizing 10-print records based upon fingerprint patterns, which reduced the effort required to search fingerprint records found in databases (IBG, 2003). The system is organized into three classification schemes: primary, secondary, and sub-secondary. The Federal Bureau of Investigation's (FBI) fingerprint system, now known as the Integrated Automatic Fingerprint Identification System, or IAFIS, is based upon the Henry system, although it has been modified for further differentiation between fingerprint cards with similar classification patterns.

2.4.1.1. Primary Classification

The first step in classification is to assign a number to each digit – the right thumb is 1, the right little finger is 5, with the left hand following the same pattern thumb (6) to the little finger (10). The goal is to pair up all 10 digits – 1 and 2, 3 and 4, 5 and 6, 7 and 8, and 9 and 10. According to the FBI (1973) the system also assigns a numerical value based on if the pattern is a whorl and which finger it is. The other two patterns, the loop and arch, receive a value of zero. Table 3 demonstrates the numerical system used in the Henry System. Using the values in Table 3, the calculation can be performed using (1), which would produce the primary group of 17/3. The Henry System can be segmented into 1,024 primary groupings (Berry & Stoney, 2001; IBG, 2003).

Table 3 Henry System's numerical values for the fingers.

	Right Hand					Left Hand				
	Thumb	Index	Middle	Ring	Little	Thumb	Index	Middle	Ring	Little
#	1	2	3	4	5	6	7	8	9	10
Whorl value	16	16	8	8	4	4	2	2	1	1
Pattern	Whorl	Whorl	Loop	Arch	Arch	Arch	Whorl	Loop	Loop	Loop
Finger Value	0	16	0	0	0	0	2	0	0	0

$$\frac{1 + (\text{Sum of even fingers with whorl patterns})}{1 + (\text{Sum of odd fingers with whorl patterns})} = \frac{1 + (16)}{1 + (2)} = \frac{17}{3} \quad (1)$$

2.4.1.2. Secondary Classification

The secondary classification scheme for the Henry System is also known as the small letter group as prints with an arch, tented arch, or radial loop in any digit besides the index finger are represented as a small letter (Federal Bureau of Investigation, 1973). Whorls are not utilized at all in the secondary scheme and ulnar loops are not recognized except if the pattern is on the index finger. The right hand is contained in the numerator, with the left hand falling in the denominator. The pattern of the index finger is listed with an uppercase letter. For example, the classification (in order from fingers 1-10) for the following:

- Tented arch (T),
- Ulnar loop (U),
- Radial loop (R),

- Radial loop (R),
- Tented arch (T),
- Tented arch (T),
- Radial loop (R),
- Radial loop (R),
- Ulnar loop (U),
- Radial loop (R),

Or $\frac{T\ U\ R\ R\ T}{T\ R\ R\ U\ R}$, would be $\frac{t\ U\ r\text{-}r}{t\ R\ r\text{-}r}$, or in simplified form would be $\frac{t\ U\ 2r}{t\ R\ 2r}$.

2.4.1.3. Sub-secondary Classification

The sub-secondary classification in the Henry system organizes or groups loops and whorls, typically in the middle and index fingers (Allison, 1973; Federal Bureau of Investigation, 1973). Classification involves ridge counting of loops and ridge (whorl) tracing of whorls. According to the FBI (1973) the ridge count is “the number of ridges intervening between the delta and the core” (p. 23). Whorl tracing depends on the placement of the deltas, which whorls typically have two or more (Federal Bureau of Investigation, 1973). Once located, the whorl is traced to determine classification as either inner or outer. For further information on sub-secondary classification consult Allison (1973) and Federal Bureau of Investigation (1973).

2.4.2. Government Classification Systems

2.4.2.1. Classification System in Great Britain

According to Allison (1973), Sir Edward Henry returned to England when he finished his service in India and subsequently published *Classification and Uses of Finger Prints*, describing the Henry System mentioned earlier in section 2.4.1. Moreover in 1900, the Belper Committee was commissioned to decide which identification system should be used in Great Britain. In 1901, the committee reported the Bertillon system should no longer be used and should be replaced by Henry's Classification System, which was in perfect coordination of Henry's book being published (Allison, 1973; Berry & Stoney, 2001). The same year, Henry was appointed Assistant Commissioner at Scotland Yard.

2.4.2.2. Argentina

Prior to the Henry System being adopted in Great Britain, Dr. Juan Vucetich, an Argentinean police officer, established a fingerprint system in the Central Police Department of La Plata, Argentina in 1891. Vucetich became interested in fingerprints through a journal article written by Galton in *Revue Scientific* that contained Galton's research on fingerprints in 1894 (Allison, 1973; Berry & Stoney, 2001). About a year later, Vucetich created a unique fingerprint system, known as "*vucetichissimo",* which utilized four fingerprint patterns as described in his book *Dactilospia Comparada* (Berry & Stoney, 2001). His system uses a combination of letters and numbers and is divided into three divisions: primary, secondary, and final, which overlap the Henry System (Allison, 1973). For further information on the Vucetich System, refer to Allison (1973). Vucetich's system is widespread throughout South America, and is often credited with being the foundation of systems created by Bertillon, Brussels, Oloriz, Lyonnese, Pessoa, and Mirando Pinto, as well as contributing to others (Allison, 1973).

2.4.2.3. Canada

The Canadians began using fingerprints in 1910, when an Order of Council passed requiring the use of a fingerprint system (Berry & Stoney, 2001). Edward Foster, known as the Father of Canadian Fingerprinting, collected and identified the first set of prints in 1911. According to Berry and Stoney (2001) after nine years of operation Foster had received more than 11,000 sets of fingerprints and identified more than 1,000 of them.

2.4.2.4. Cuba

In 1904, the Cuban fingerprint pioneer, Juan Francisco Steegers y Perera introduced a fingerprint system to identify delinquents. According to Berry and Stoney (2001) a commemorative booklet issued by the Cuban Ministry of Communications in 1957 outlined Steegers as the first to introduce dactyloscopic information, which his research created a new dactyloscopic-photographic medium.

2.4.2.5. United States of America

2.4.2.5.1. New York City's Civil Service

The United States entered the world of fingerprinting for identification in 1902. However, the program was limited to the state of New York, specifically New York City's Civil Service Commission. Dr. Henry de Forest, the Chief Medical Examiner, implemented the fingerprint system in order to prevent people, except the patient filing the application from receiving an examination (Allison, 1973).

2.4.2.5.2. New York Prison Department

The New York State Prison System was introduced to fingerprints in March of 1903 by Captain James Parke. Parke received his information and training from Baker and Lamb which according to Allison (1973) were sent to Europe to study the fingerprint system of Cornelius Collins, who was the Superintendent of Prisons. When Baker and Lamb returned they had copies of Galton's *Finger Prints* and Henry's *Classification and Uses of Finger Prints*. Parke modified Henry's system which formed the basis of the American system.

2.5. The Integumental System

Before a biometric system can acquire a sample from an individual, an individual must present their biometric characteristic(s) or trait(s) to the sensor. This research focuses on fingerprint recognition, thus the acquired characteristics or traits are physiological. Fingerprints are part of the human skin; thus this section will focus on the anatomy and function of the human skin. The human body consists of eleven classified systems of organs that carry out complex functions. The Integumental system includes skin, hairs, nails, sweat and sebaceous glands; subcutaneous fat and deep fascia; the mucocutaneous junctions around the openings of the body orifices; and the breasts (Standring, 2004). The human skin, classified as an organ, is the heaviest in the body, ranging between eight to sixteen percent of the total body mass of an individual (Standring, 2004; Zhang, 1999).

2.5.1. The Skin

The skin is one of the best indicators of general health and is an effective protector against biological, chemical, mechanical, osmotic, thermal, and Ultra-Violet (UV) radiation damage (Standring, 2004; Swartz, 2001; Zhang, 1999). Other important functions of the skin include regulation of body temperature and a receptor to touch, pressure, pain, and temperature stimuli (Standring, 2004; Zhang, 1999). The skin can be classified into two types: thick and thin; and ranges in thickness from approximately 1.5 mm to 4.0 mm, dependent upon the area of the body, maturation, and aging (Standring, 2004). Thick, or glabrous, skin is only found in areas of the body that do not contain hair, which are the palms of the hands, flexor surfaces of the digits, and soles of the feet. Thin, or hirsute, skin covers the rest of the body. The structure of thick and thin skin can be found in Figure 13. Further examining the skin, it can be differentiated into two main layers: the dermis and epidermis.

2.5.2. Dermis

The "*dermis*", which is Greek for skin, is the thick layer that serves as the foundation for the upper layers. The dermis contains arteries and veins; blood capillaries and vessels; lymphatic capillaries; and nerve fibers (Ashbaugh, 1991; Zhang, 1999). The main functions of the dermis are to provide strength and elasticity to the skin. Various collagen fibers and arrangements provide the tensile strength to the skin, while elastic fibers allow the skin to deform and return to its original shape. The density of the fibers and arrangements varies across the body, by sex, and with age (Standring, 2004). Moreover, Ashbaugh (1991) mentions the ridges and furrows have their roots in the dermis, meaning the pattern of the friction ridges are formulated long before reaching the outermost, or cornified, layer. However, while the ridges are formed before they reach the cornified layer, Ashbaugh (1991) states that

> Cuts that penetrate completely through the bottom layer of the epidermis and reach the dermal papillae [in the dermis] will leave a scar as new healthy skin cells cannot be regenerated due to the cell damage in the generating layer" (p. 26).

Therefore if a cut penetrates through the epidermis down to the dermis, the friction ridge will be altered, which may cause problems for fingerprint recognition algorithms. Moreover, Moore and Dalley (2006) discuss the effects of aging on the skin, stating “the elastic fibers of the dermis deteriorate with age and are not replaced; consequently, in older people the skin wrinkles and sags as it loses its elasticity” (p. 13). This can also negatively affect fingerprint recognition performance, as individuals may not be able to produce repeatable samples, which is discussed in sections 2.6.3.1 and 2.6.4.3.

The dermis consists of three layers: the papillary layer, reticular layer, and the hypodermis, also known as the superficial fascia. The three layers will be discussed next from the deepest layer to the outermost layer.

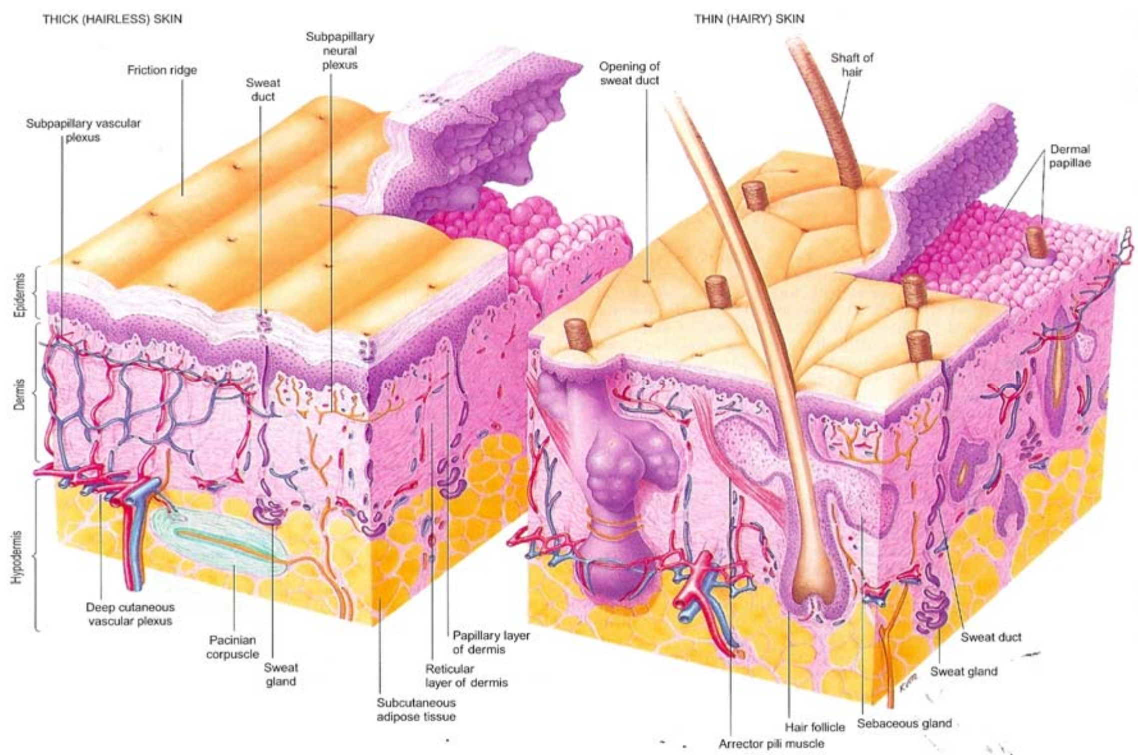


Figure 13 The structure of the thick or hairless skin (left) and the thin or hairy skin (right) (Standring, 2004).

2.5.2.1. Hypodermis

The hypodermis is composed of loose connective tissue called subcutaneous tissue, which is of varying degrees of thickness. The main functions of the hypodermis are for:

- Thermal insulation,
- Shock absorption,
- Storage for metabolic energy, and
- Mediating the mobility of the skin (Standring, 2004).

The hypodermis varies in density across the body. According to Standring (2004) the hypodermis is "particularly dense in the scalp, palms, and soles, where it is crossed by numerous strong connective tissue bands binding the hypodermis and skin to underlying structures" (p. 163).

2.5.2.2. Reticular Layer

The reticular layer connects the deep tissues of the hypodermis to the papillary layer. This layer consists of large bundles of collagen fibers which interact with the collagen found in the papillary layer to form a strong yet deformable three-dimensional lattice (Standring, 2004). In adults, eighty to eighty-five percent of collagen is Type I, which is coarser than Type III, which is found in the papillary layer (Standring, 2004).

2.5.2.3. Papillary Layer

The papillary layer is proximate to the epidermis and provides structure to the skin, metabolic support, nutrition, as well as supplies sensory nerve endings and blood vessels (Standring, 2004). Another minor type of collagen (type VII) links the epidermis deep into the papillary dermis and provides a strong foundation for the epidermis (Standring, 2004). The strength of the epidermis is due to the two rows of papillae (rete ridges) of the dermis on each side of the epidermal rete pegs that lie under each epidermal ridge. It is here where the dense collagen fibers are located and provide strength to the epidermis (Standring, 2004; Zhang, 1999). The rete ridges of the dermis join the rete pegs of the epidermis much like two connecting puzzle pieces interlock.

2.5.3. Epidermis

The "*epidermis*", which is Greek for upon the skin is a compound tissue that consists of mostly self-renewing cells, called keratinocytes (Standring, 2004). The epidermis consists of several small layers, where keratinocytes continually produce new cells, which begin formation in the innermost layer (basal layer) and continually change until reaching the outermost layer (cornified or horny layer). In this layer, a substance called desmosome prevents skin cells from dispersing immediately after reaching the cornified layer (Ashbaugh, 1991). The layers of the epidermis are: basal layer, spinous or prickle cell layer, granular layer, clear layer, and the cornified layer (Standring, 2004).

2.5.3.1. Basal Layer

As previously mentioned, the basal layer is the innermost layer of the epidermis, which is adjacent to the dermis (papillary layer) and is where cell production occurs. This joint area of the epidermis and dermis is complex, especially in the thick skin, as the dermal papillae project into this layer to interlock with the rete pegs of the basal layer, which is shown in Figure 14 (Standring, 2004).

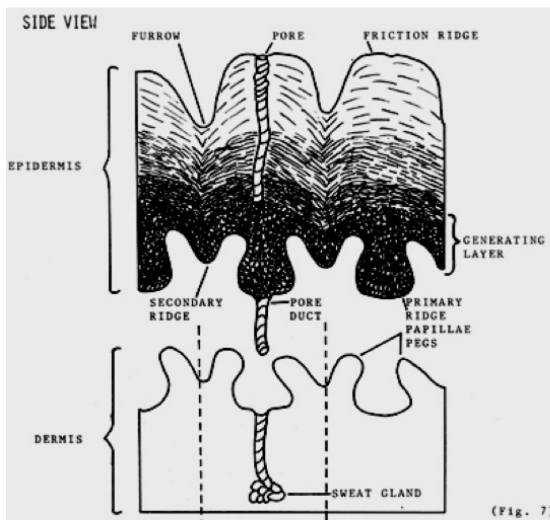


Figure 14 Side view of the complex interface of the epidermis and dermis (Ashbaugh, 1991).

2.5.3.2. Prickle Cell Layer

The prickle cell layer is proximate to the basal layer and consists of numerous layers of closely packed keratinocytes, which project upwards from the basal layer. This layer provides tensile strength and cohesion to the epidermis (Standring, 2004).

2.5.3.3. Granular Layer

The main function of the granular layer is to form a permeable barrier (Standring, 2004). Other functions of the granular layer, while interesting, are outside the scope of this study. For more information, refer to Standring (2004).

2.5.3.4. Clear Layer

According to Standring (2004), the clear layer “represents a poorly understood stage” (p. 160). This layer is located in thick skin of the hands and feet only.

2.5.3.5. Cornified Layer

The outermost layer of the epidermis and skin is the cornified layer. This layer is approximately fifty cells deep in thick skin and only a few cells deep in the thin skin (Standring, 2004). Moreover, according to Standring (2004) cornified layer thickness is affected by environmental factors, such as abrasion, which leads to epidermal thickening of the whole epidermis, commonly called calluses. This layer also consists of keratinocyte cells, called squames that interlock with each other. Figure 15 reveals an image of a human digit and the closely packed squames, as well as friction ridges and sweat pores.

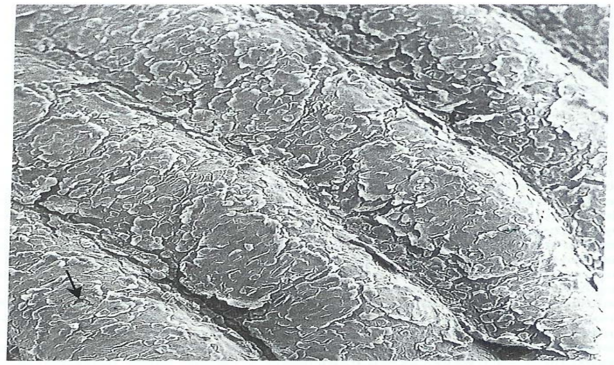


Figure 15 Fingerprint image taken with a scanning electron microscope showing the cornified layer of numerous squames, friction ridges, and a sweat pore [indicated by an arrow] (Standring, 2004).

2.5.4. The Sweat Glands and Pores

Sweat glands are rooted deep in the dermis in the hypodermis layer. The tubular structure, or duct, passes up through the dermis and into the epidermis, which opens on the surface of the skin, which is known as a pore. The tubular structure can be up to 0.4 mm in diameter with the pore opening being narrower (Standring, 2004). Pores contained in the skin of the volar areas of the palms and feet only appear in ridges in order to provide the support of the pore opening, which is shown in Figure 16. The role of sweat glands in the body is for regulation of body temperature and contribute “significantly to excretion and their secretion enhances grip and sensitivity of the palms and soles” (Standring, 2004, p. 166). The frequency of pores in the skin varies from eighty to over six hundred per square centimeter, with total number between 1.4 and 4.5 million and is dependent upon area of the skin and genetic variation (Standring, 2004). Moreover, Standring (2004) states that certain races that live in warmer climates tend to have more sweat glands than those in cooler regions.

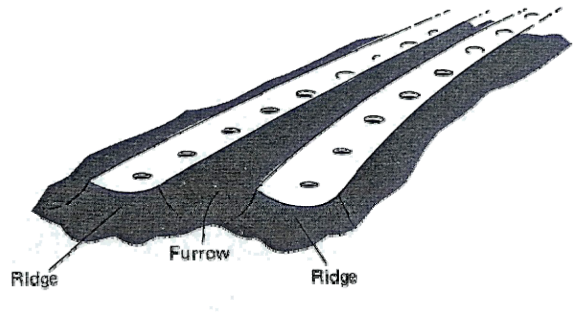


Figure 16 Illustration of friction ridges and furrow with pores (Allison, 1973).

2.5.4.1. Poroscopy

Pores have also been studied as a method of identification. Dr. Edmond Locard of Lyon, France in 1912 established the science of poroscopy and suggested that pore size, shape, relative position, and frequency of appearance or pores could be used to identify individuals (Ashbaugh, 1991). Moreover, Ashbaugh (1991) states numerous studies have shown that pores can be used to identify individuals, however “pore structure does not record accurately enough in inked or crime scene prints to facilitate this type of absolute comparison and evaluation” (p. 48). While Ashbaugh discussed inked prints, there was no mention of automatic capture of fingerprints through the use of biometric devices. Current fingerprint recognition technologies can capture sufficient pore detail, which can be used for identification, as depicted in Figure 17.

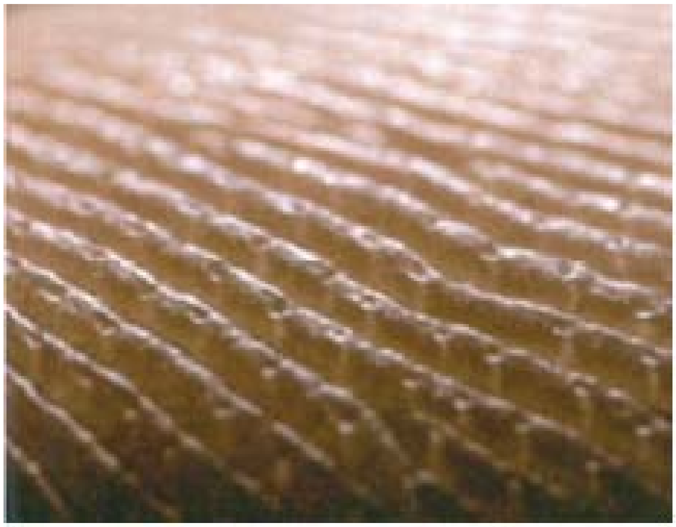



Figure 17 Magnified finger image showing friction ridges and pores (left) (Mainguet, 2006). Right thumbprint showing pore detail (right).

2.5.5. Skin and Friction Ridge Development

In 1929, Cummins published a report in *Contributions to Embryology* which discusses the formation of the volar pads of the human hands and feet. In this report titled “Topographic History of the Volar Pads (Walking Pads; Tastballen) in the Human Embryo” Cummins states that the thick skin of the digits and palms appear in their typical formation around the sixth week of gestation up until around the thirteenth week when the pads begin to regress (Cummins, 1929). During the first four to five weeks the embryonic epidermis consists of a layer of cells that is one cell deep (Ashbaugh, 1991; Standring, 2004). As fetal development continues, the epidermal cells divide and grow, thickening this layer. The primary ridges begin to develop during the second and thirds months on the hands and feet (Standring, 2004). Primary ridges develop pores and lie underneath the surface friction ridges (Ashbaugh, 1991). As gestation continues, the secondary ridges develop around the fifth month between the primary ridges, which do not develop pores or become as large as the primary ridges (Ashbaugh, 1991; Standring, 2004). The primary ridges supply kertatinocyte cells to the surface friction ridge areas, while the secondary ridges supply cells to the surface friction ridge furrows (Ashbaugh, 1991). The primary and secondary ridge structures are shown in Figure 18.

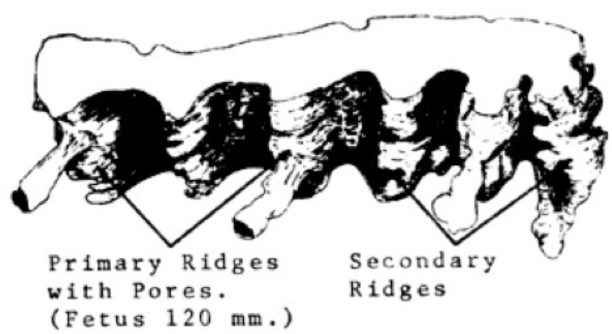


Figure 18 Fetal development of friction ridges: primary and secondary (Ashbaugh, 1991).

2.5.6. Skin Aging

According to Standring (2004) there are two main factors that cause skin aging: chronological and environmental. The first, chronological changes, are physiological (intrinsic) in nature, while the latter are dependent upon external factors; such as exposure to the sun.

2.5.6.1. Physiological Factors

The natural aging process begins around the age of 30 where the skin undergoes gradual changes in appearance as well as the mechanical properties. Natural aging is characterized by epidermal and dermal atrophy causing changes in appearance, structure, and function; which include wrinkling, dryness, loss of elasticity, thinning, and a tendency towards bleeding under the skin (purpura) when minor injuries or trauma are sustained (Standring, 2004).

Dermal atrophy is characterized by “general thinning and loss of the basal rete pegs [Figure 14 labeled primary papillae rete pegs in the dermis] with flattening of the dermo-epidermal junction” (Standring, 2004, p. 175). The results of this can affect epidermal nutrition. Moreover, the flattening of the junction “decreases resistance to shear, leading to poor adhesion of [the] epidermis and its separation following minor injury” (Standring, 2004, p. 175). While the thickness of the cornified layer does not reduce during the aging process, cell replacement can be reduced up to fifty percent (Standring, 2004). As mentioned above, dermal atrophy can affect epidermal nutrition, thus is mainly responsible for appearance and mechanical properties changing, especially the skin’s stiffness, flaccidity, wrinkling, and loss of elasticity. While the thickness of the cornified layer does not decrease, the dermis does in general as a result of a decline in collagen synthesis of Type I, which is the coarser and provides the tensile strength in the dermis (Standring, 2004).

Summarizing the physiological changes of the skin – atrophy of the dermis occurs which causes a loss of strength at the dermal and epidermal junction. In addition Type I collagen declines with age, causing the dermis to lose its strength. Thus, these two factors along with others cause aging skin to deform and wrinkle, which affects image quality and performance of fingerprint systems.

2.5.7. Ridge Characteristics

While the skin forms in a predetermined process, ridge alignment and shape; minutiae location, and the location of pores all occur randomly (Ashbaugh, 1991). More importantly, these variables define most of the characteristics for the three levels of classifying fingerprints.

2.5.7.1. Level 1 – Patterns

The first level of classification is the overall pattern of the fingerprint, or ridge configuration. All fingerprints fall under three patterns: arches, loops, and whorls. Finger patterns were discussed in sections 2.3.1.6 and 2.3.1.8. Figure 19 shows the three pattern types.

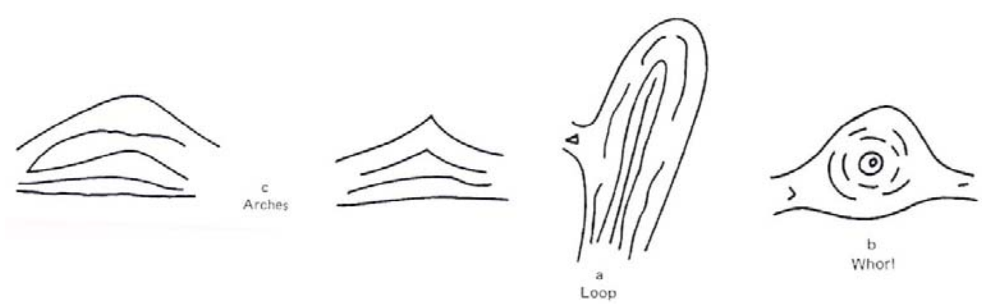


Figure 19 Three types of pattern lines in fingerprints (Allison, 1973).

2.5.7.2. Levels 2 – Minutiae Type and Position

The second level of classification examines the fingerprint more closely, specifically the minutiae. Minutiae points were discussed in section 2.3.1.8 as Galton features.

2.5.7.3. Level 3 – Shape of Minutiae, Ridges, and Location of Pores

The third level of detail for classification looks even more closely at the structure of the fingerprint and examines individual minutiae on the ridges as well as locations on the pores. With biometric systems, each minutiae based algorithm operates uniquely and locates, identifies, and maps minutiae differently.

2.5.8. Ridge Permanence

Many of the nineteenth century fingerprint pioneers were intrigued by how well fingerprints withstood the test of time, as well as being purposefully damaged. The following subsections will discuss experiments in ridge permanence and are presented in chronological order.

2.5.8.1. Dr. Henry Faulds

Faulds performed research on the permanence of fingerprints. In one experiment conducted by Faulds, he fingerprinted patients, removed the skin of the fingertips, and fingerprinted them again when the skin healed, and noted that the details of the ridges were in the exact same position as the earlier set of prints (Berry & Stoney, 2001).

2.5.8.2. Sir William Herschel

Herschel also conducted experiments on the permanence of prints; taking his palm impression in 1860 and again in 1890 with the ridge pattern remaining the same, however creases appeared on the fingers and palms and the ridges appeared to be coarser than the earlier print (Berry & Stoney, 2001; Galton, 1892; Morland, 1950).

2.5.8.3. Welker

A third individual, a German anthropologist named Welker experimented with the permanence of fingerprints, taking his own palm impression in 1856 and again in 1897, which again revealed no changes in ridge detail on the palm and hand (Berry & Stoney, 2001; Morland, 1950).

2.5.8.4. Dr. Leonard and Dr. Witkowski

Even more painful than Faulds's experiment, Dr. Leonard, a student of Bertillon, who later explained the existence of trace evidence at crime scenes, along with Dr. Witkowski of Lyon, France conducted experiments on the permanence of fingerprints. According to Morland (1950) these experiments "subjected their fingers to the action of boiling water, hot oil, and to pressure on hot plates" (p. 26). While the epidermis was damaged, the corium, or true skin, remained unaffected by the harsh treatment that was exposed to the fingers (Morland, 1950, , 1971). Once the new tissue grew, the original friction ridge pattern returned as it was prior to the exposure to the hot materials.

2.5.9. Testing the Permanence of Fingerprints

2.5.9.1. Roscoe Pitts

The Federal Bureau of Investigation (FBI) in 1941 had a case that dealt with the permanence of fingerprints. Roscoe Pitts, a man with multiple identities, was arrested on the charge of for not being registered in the U.S. Selective Service program. More interestingly, Pitts was found to have no fingerprints, just scars which appeared to be from surgery (Morland, 1950). When compared against previous files, a record matching Pitts was found with fingerprints. In an attempt to evade law enforcement Pitts hired a New Jersey doctor named Brandenburg to cut the flesh of Pitts's fingers down to the bone and attach them to the side of his chest (Morland, 1950). When the tissue had healed, the fingers were removed from the chest, resulting in Pitts now having no fingerprints, however what remained were very unique and identifiable scars.

2.5.9.2. John Dillinger

In a similar case, John Dillinger, a notorious and vicious thief from the Midwest, had extensive plastic surgery on his fingers to remove his fingerprints. However, when examined, the underlying tissue of the corium remained undamaged, and the scars left by surgery made identification even more exact (Morland, 1950).

2.6. The Biometric Model

Applying fingerprint classification to a biometric system functions in a similar manner to the other biometric modalities. A general biometric model was originally proposed by Mansfield and Wayman (2002) to visually represent and explain the functionalities in a biometric system, which is shown in Figure 20; and has been subsequently modified in ISO 19795-1 (2006a), and shown in Figure 21. In general, there are five internal processes or sections in a biometric system: data capture, signal processing, data storage, matching, and decision.

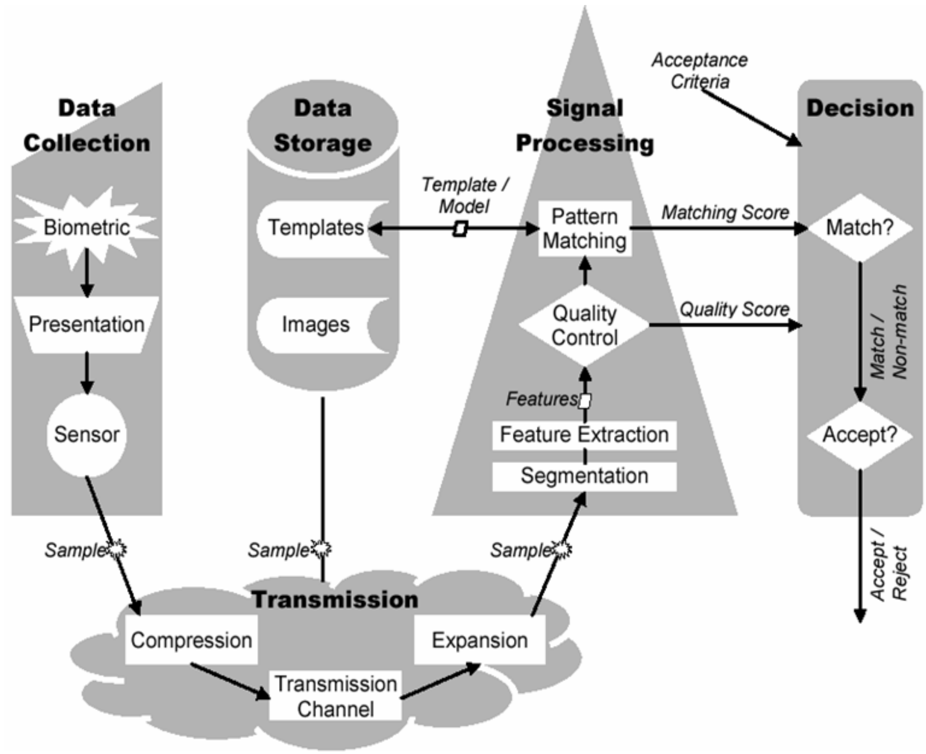


Figure 20 The general biometric model (Mansfield & Wayman, 2002).

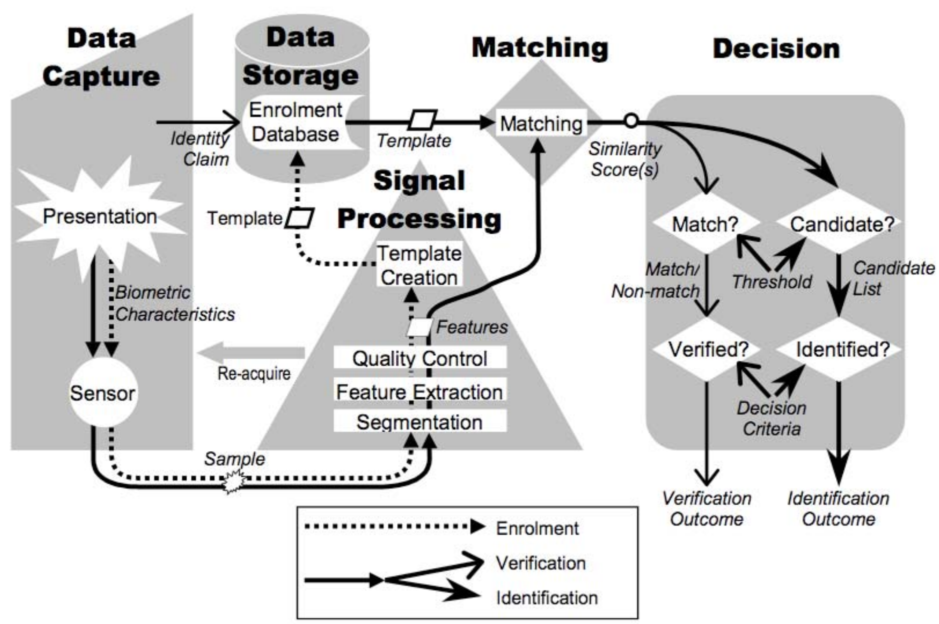


Figure 21 Updated general biometric model (International Standards Organization, 2006a).

2.6.1. Data Capture

Navigating through the model, an individual first presents their biometric characteristic(s) to a sensor, camera, or other collection device. In order for a biometric system to function, it must capture the physiological or behavioral characteristic(s) of interest, for example fingerprints, voice patterns, face or iris images, or an electronic signature. Once the system acquires the characteristics from the sensor, the sample transfers to the signal-processing silo. However, before signal processing is discussed, the different fingerprint acquisition devices will be discussed.

2.6.2. Sensors - Fingerprint Acquisition Source

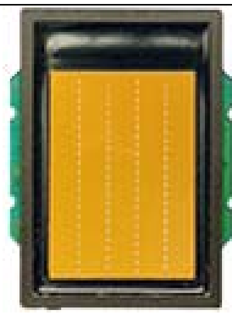
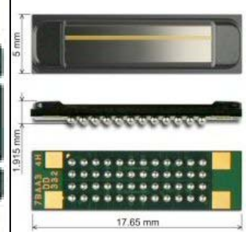
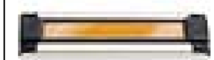
The next component of the biometric model is the sensor. Biometric sensors include an expansive list of devices, including simple microphones for voice recognition, web cameras for iris and face recognition, optical and capacitive sensors for fingerprint recognition, and expensive sensors like stereoscopic high-resolution cameras (three dimensional face recognition).

Since modern fingerprinting began in the late nineteenth century, many methods of collection have been utilized, which fall under two main categories: inked impressions and live-scan images (inkless impressions). The first category, inked impressions, includes methods which are used by law enforcement. The most basic type of inked impressions are created by physically applying ink to fingers and rolling, dabbing, or slapping a finger or group of fingers on a substrate. Other methods of fingerprint acquisition for forensic science applications emerged in the 1950s for crime scene investigations which used mercury-based white powders which have been discontinued due to the health hazards (Berry & Stoney, 2001; Rabjerg, Jennum, & Morck, 1983; Thomas, 1978). Developments soon appeared using a mixture of ninhydrin and fluorisol, commonly known as Freon in the United States. Ninhydrin reacts with amino acids found in perspiration causing a colored imprint to form on the paper, while the Freon prevents ink from smudging on paper (Berry & Stoney, 2001). Other developments over the last fifteen years include a technique detectives in Great Britain use, which uses a Camtac machine that “lifts” the fingerprint as a negative and can produce an enhanced copy of the fingerprint in ninety seconds with acceptable ridge detail (Berry & Stoney, 2001). Other techniques to enhance and collect latent fingerprints include: cyanoacrylate, or superglue fuming, black and light colored powders depending on the color of the surface, and magnapowder, which black powder mixed with metal shavings for use on shiny surfaces (Lee, Palmbach, & Miller, 2003).

The second category of prints is live-scan or inkless prints, which is associated with biometrics, as fingerprint acquisition is automatic. Of the five common families of fingerprint sensors optical, capacitance, thermal, ultrasound, and touchless, the two most widely used are optical and capacitance; they tend to be used for specific and exclusive applications. Optical sensors are more commonly used in law enforcement, border control, and desktop authentication applications, whereas capacitance sensors are found in laptops, cellular phones, personal data assistants (PDAs), and flash drives. There is some degree of overlap between capacitance sensors and optical sensors, particularly in access control and desktop security applications.

Furthermore, over the last few years the size of fingerprint sensors has decreased. This can be attributed to a number of factors, such as an increase in applications that require different sizes due to available space, as well as a reduction of raw material cost, to name two. Table 4 shows four capacitance-based sensor images in decreasing size, as well as lists the technical specifications for each respective sensor. One may ask “which sensor is best?” The answer depends on many factors, some of which include: the intended application, the available space for a sensor, and the available power, to name a few.

Table 4 Range of sensor sizes and specifications (UPEK Inc., 2007).

	Large Area Sensor	Medium Area Sensor	TouchStrip™ Fingerprint Authentication Solution	TouchStrip Strip Sensor
ID	**TCS1**	**TCS2**	**TCS3-TCD42**	**TCS4**
Picture				
Size	20.4 x 27 x 3.5 mm	20.4 x 27 x 3.5 mm	17.65 x 5 x 1.915 mm (TCS3) 10 x 10 x 1.26 mm (TCD42)	14 x 4.5 x 1.5 mm
Active Array Size	12.8 x 18.0 mm	10.4 x 14.4 mm	12.4 x 0.2 mm	9.6 x 0.2 mm
Array size	256 x 360 pixels	208 x 288 pixels	248 x 4 pixels	192 x 4 pixels
Power supply	4.4V ~ 5.5V*	4.4V ~ 5.5V	2.7V ~ 3.6V	2.4V ~ 3.6V
Imaging	20mA @ 5V	20mA @ 5V	<156mA @ 3.3V (Sensor <51mA, Companion Chip <105mA)	11mA
Operating Temps	-30°C to +85°C	-30°C to +85°C	TCS3: -30°C to +70°C TCD42: -40°C to +85°C	-30°C to +70°C
Acquisition speed	14 frames/sec	15 frames/sec	20 cm/sec	20 cm/sec typical
Image Resolution	508 DPI			
Technology	CMOS active capacitance pixel-sensing			

2.6.2.1. Optical

Optical technologies were the first live-scan method used due to the adoption of the Federal Bureau of Investigation's Automatic Fingerprint Identification System (AFIS), now known as IAFIS during the 1960s. According to Bolle, Connell, Pankanti, Ratha, and Senior (2004), one the first uses of optical technologies besides law enforcement was in medicinal studies in 1966.

The technology behind optical sensors is similar to that of digital cameras, as typically a charged coupled device (CCD) or complementary metal oxide semiconductor (CMOS) camera is used to image the finger. Imaging is possible through the use of a prism which the user places their finger on. A light source, typically a light emitting diode (LED) illuminates the finger, specifically the friction ridges that are placed upon the prism (platen). The Frustrated Total Internal Reflection (FTIR) is the reflection caused by the presence of ridges and valleys on the prism, which is shown in Figure 22. The ridges appear dark in the resulting image, while the furrows appear clear or white. The main issues surrounding optical technologies, which are based on reflection, are a function of personal skin characteristics such as dry and moist or sweaty fingers (Bolle, Connell, Pankanti, Ratha, & Senior, 2004) According to Bolle et al. (2004), "if the skin is wet or dry, the fingerprint impression can be "saturated" or faint, respectively, and hard to process" (p. 33).

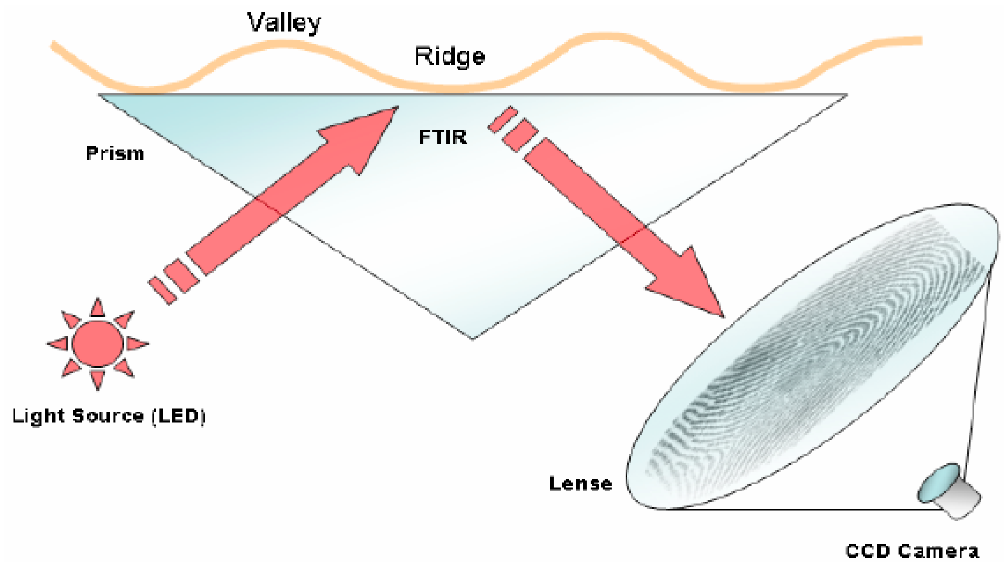


Figure 22 Optical fingerprint technology using FTIR (Elliott, Sickler, Kukula, & Modi, 2005)

Depending on the purpose of the imaging system, the size will vary for dabbed, slapped, or rolled prints. The platen or prism size for dabbed optical technologies is typically the smallest within the optical technologies, but largest for the various fingerprint technologies, with an average acquisition surface of one square inch. The United States Visitor and Immigrant Status Indicator Technology (US-VISIT) program uses a sensor with a 1.2 square inch prism.

2.6.2.2. <u>Ultrasound</u>

Ultrasound (ultrasonic) sensing techniques utilize ultrasonic energy to detect the fingerprint pattern as the energy in the form of a beam passes across the finger surface to measure the depth of the valleys from the reflected signal (Bicz, Gurnienny, & Pluta, 1995; Setlak, 2004). According to Setlak (2004), there are two main types of ultrasonic systems. The first examines the differences in ultrasonic absorption between the ridges and valleys. The second is based upon echo reflection techniques that generate images of the internal layers of the skin. The benefit of ultrasonic sensors is that wet and dry skin conditions do not affect imaging, and they could possibly be implemented as a non-contact sensor (Bicz, Gurnienny, & Pluta, 1995; Bolle, Connell, Pankanti, Ratha, & Senior, 2004). However, current ultrasonic technologies are bulkier, more expensive than other available technologies, and require more time for imaging a finger than other technologies (Bicz, Gurnienny, & Pluta, 1995; Setlak, 2004).

2.6.2.3. Thermal

Thermal sensing techniques utilize pyroelectric material that measure changes in temperature, called thermal energy flux, to detect the pattern of ridges and furrows of a finger when swiped across a sensor (Bolle, Connell, Pankanti, Ratha, & Senior, 2004; Mainguet, Pegulu, & Harris, 1999; Setlak, 2004). Thermal sensors use the properties of skin beneficially, as skin is a better conductor than air. Therefore, when ridges contact the heated thermal sensor, a difference is realized, as heat dissipates and flows between the ridges in contact with the sensor surface (Bolle, Connell, Pankanti, Ratha, & Senior, 2004; Mainguet, Pegulu, & Harris, 1999; Setlak, 2004). According to Setlak (2004) the change in temperature “can be measured by an array of tiny differential sensors and converted into an electrical signal” (p. 30).

2.6.2.4. Capacitance

Electrical fingerprint sensing have several advantages over mechanical, optical, thermal, and ultrasonic techniques when integrated with other electrical components as the electrical sensing mechanisms do not need to be converted into an electrical form of energy (Setlak, 2004). Electrical sensing technologies began to emerge according to Setlak (2004) in the late 1960s. One of the seminal patents in conductive sensing technologies was granted to Killen (1973) that describes an array of conductive sensing spots that captured fingerprint information. This work was advanced in the 1980s through patents by Tsikos (1982) and Abramov (1986). Please see the patent sources and Setlak (2004) for further information.

According to Setlak (2004), capacitive fingerprint sensors were in a sense able to be conceived due to researchers work on memory devices and chips during the 1980s. The researchers:

> Discovered (undoubtedly by accident, as the touching of a semiconductor chip usually contaminates it beyond recovery) that a finger placed on top of the memory array caused data errors that followed the spatial pattern of the fingerprint. Recall that dynamic random access memories (DRAM) use a periodically refreshed charge stored on a small capacitor in the memory cell; clearly, the differences in capacitance between a ridge or valley and the individual memory cell caused bit flips in some cells (Setlak, 2004, p. 33).

Electrical fingerprint sensors can be categorized into three technologies; conductive, capacitance, and Radio Frequency (RF) imaging (Setlak, 2004). As this research uses only capacitance technologies, subsequent discussion will be limited to such technologies only.

The first commercial capacitance sensors became available during the 1990s, which according to Setlak (2004) are “constructed using a two-dimensional array of small conductive plates covered by a thin dielectric protective layer” (p. 33). When the finger is placed above the array of sensors, the ridges make contact and the valleys do not, which pass an electrical charge through the sensor, which is shown in Figure 23. More specifically, there are two classes of capacitance finger sensors: single plate and double plate, or differential. In single plate sensors, each sensor plate corresponds to a particular pixel in the fingerprint image where the electrical charge of each plate is measured and compared to ground, the typical global environment (Setlak, 2004). The other class is known as double-plate sensors, which utilize two adjacent sensor plates that correspond to a particular pixel in a fingerprint image. Whereas the single plate method measures the electrical charge of the fingerprint using ground, double-plate sensors use the capacitance between the two plates to generate the value of the pixel (Setlak, 2004).

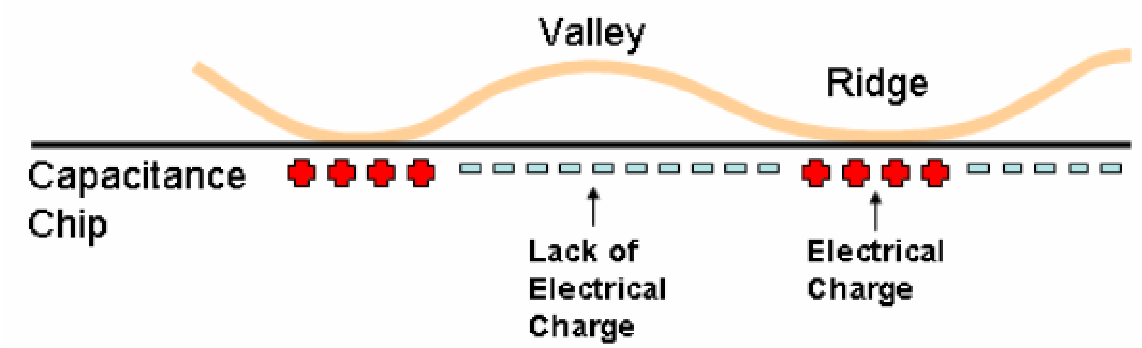


Figure 23 General capacitance fingerprint sensor (Elliott, Sickler, Kukula, & Modi, 2005).

UPEK's sensors, which were used in this study, are classified as double-plate active capacitance sensors. In UPEK's patent, which is assigned to STMicroelectronics, Inc. double-plate active capacitance sensors are described as follows:

> The input and output of the solid state amplifier are respectively connected to two relatively large and ungrounded capacitor plates, or electrodes, that are associated with, but physically and electrically isolated from, the switch's external dielectric surface. A person's ungrounded fingertip forms a third capacitor plate on, or closely adjacent to, the switch's external surface. The solid state amplifier circuit detects the presence of a fingertip on the switch's external surface by way of a change in capacitance that is created within a compound, three electrode or three plate, capacitor that includes the two ungrounded capacitor plates and the ungrounded fingertip that is closely adjacent to, or resident on, the switch's external surface (Gupta & Kramer, 1999).

For more information regarding UPEK's active capacitance sensors, please refer to patent 5,973,623 (1999).

2.6.3. Presentation

The focus of this dissertation surrounds how users interact with the biometric system, primarily how they present their characteristics to a biometric sensor. In general, a sensor can be either covert, meaning the user may not be aware that a sensor is collecting their biometric characteristics, for example face recognition where photographs are taken without approval of the individual being photographed, or overt, meaning the user is fully aware of an interaction taking place with a biometric sensor. The goal of the presentation stage is for a user to present their biometric characteristics to the sensor in a repeatable and consistent manner to produce images or samples that are of sufficient or high quality. Good quality images are important to collect during presentation so that the subsequent signal-processing sub-processes, including: segmentation, feature extraction, and quality control can successfully occur. In the case of fingerprint recognition, the sensor, the enclosure, or form factor, and the cues or guidance provided by the sensor/system, facilitate the presentation.

2.6.3.1. Problems Presenting to the Sensor

2.6.3.1.1. Biometric Properties and Ergonomic Implications

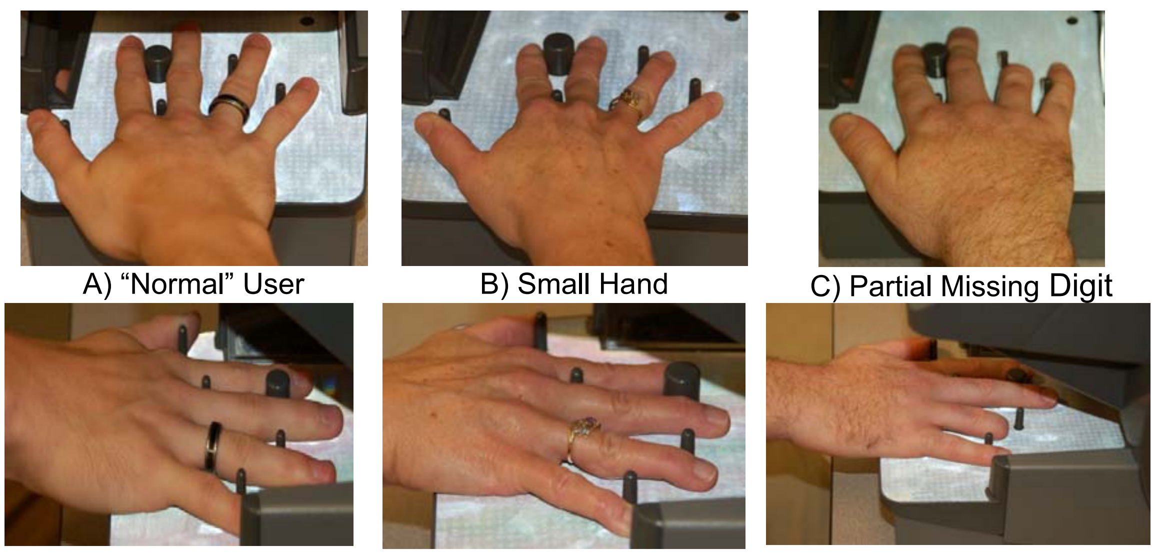
In addition to classifying biometric modalities as either physiological or behavioral, the technologies can also be classified by five desirable properties, outlined by Clarke (1994) which are:

- Universal,
- Unique and exclusive,
- Permanent over the course of one's life,
- Collectable and digitally storable, and
- Acceptable to social standards.

While these five properties have been well established in the biometrics community, the majority of biometric sensors and systems, as a whole, still have problems satisfying these criteria. Moreover, these five properties have not been exhaustively researched to the point where issues and problems with biometric sensors and systems can fully be understood. Consider the following cases that challenge the performance of a biometric system.

2.6.3.1.2. Universality of biometric characteristics

Not everyone will necessarily have a particular biometric trait. Alternatively, an individual's biometric trait may be significantly different from the "average" expected trait. For example, in hand geometry, an individual might be missing a digit, which could cause the acquisition problem of a FTA. A hand geometry system requires the user to place his or her hand on the platen such that all of the digits touch all of the guide pins simultaneously for a set period of time (Figure 24a). If the digits do not touch all of the guide pins, then the individual with small hands (Figure 24b) or missing digits (Figure 24c) must compensate by rotating the hand, causing either ulnar or radial deviation of the wrist. While the effects of the wrist deviation may cause only slight discomfort during each interaction, over time, the motion may cause damage that is more lasting, possibly resulting in a musculoskeletal disorder (MSD). In terms of biometric system performance, this hand/wrist rotation and deviation causes image repeatability problems — each time the user interacts with the device, the resulting image will be different.



A) “Normal” User | B) Small Hand | C) Partial Missing Digit

Figure 24 Top and Side Views of a “Normal” User (left), Problematic User with Small Hands and CTS (center), and Problematic User with Partial Missing Digit (right).

An individual may not be able to produce a repeatable hand placement due to disorders such as carpel tunnel syndrome or arthritis. One specific case is shown in Figure 24b. This individual is afflicted with carpal tunnel syndrome (CTS) and reported some discomfort when interacting with the platen, as this individual has small hands, therefore had to stretch their hand and fingers to touch each of the guide pins in order to pass the system requirements. Successful enrollment may be difficult to repeat due to pain or stiffness in the hand or fingers, which could result in an increase in either the false rejection rate (section 2.8.4.2.2.6) or failure to enroll rate (section 2.8.4.2.2.1). If the user cannot touch all the pins at the same time, then the system will time out, causing a Failure to Acquire (section 2.8.4.2.2.2).

It is almost impossible to assess which characteristics a population will or will not exhibit; this means there is no guarantee of universality of a particular biometric characteristic. Only empirical data and experience can aid in resolution of matters involving universality.

2.6.3.1.3. Variability of biometric characteristics

Although it is desired for a biometric characteristic to be stable over time, this may be difficult to achieve. Over time, general and occupational wear can alter or change characteristics. An individual can also alter their appearance by growing facial hair, losing weight, injuring specific features, such as cutting or scarring a finger, or intentionally altering the way an individual walks (gait) or signs their name. In the case of fingerprints, occupational wear and tear or aging can cause scarring or wrinkling of fingerprints, which may affect its image quality, ultimately affecting the performance of the biometric recognition algorithm. Figure 25 provides an example for age and image quality of fingerprints. In this example, one can visually see a difference in the raw images (Figure 25a and c). Figure 25a is an image of a 22 year old, which is supple and of good quality. Alternatively, Figure 25c is a fingerprint image of an 88 year old and has many wrinkles. When the biometric system processes the images, the system returns a processed image with minutiae points (circles) located (Figure 25b and d). Examining the processed image of the 88 year old (Figure 25d), the wrinkles have been mapped as minutiae points.

The receiver operating characteristic (ROC) curve is a graphical representation of the performance of a biometric system and is further discussed in section 2.8.4.2.2.3. Figure 26 shows the ROC curves of the algorithm's performance on the populations typified by these two fingerprints. Line (a) shows the 18-25-year-old population; line (b) shows the 62 and older population. Note that line (b) is shifted up and to the right, indicating poorer performance of the algorithm on that age group, compared to the algorithm's performance on the age group represented by line (a). This poses a potential problem as the wrinkles may change shape or location over time, posing a problem for fingerprint recognition systems. Moreover, the way in which an individual presents his/her finger to the device can potentially cause problems for the biometric system. For example, if an individual does not provide uniform contact (pressure or speed) when interacting with a fingerprint sensor, the system may capture an image of insufficient quality, which can be seen in Figure 27. In addition to non-uniform contact, a dry finger may also look similar to the left image in Figure 27. For more discussion on fingerprint image quality and performance see section 2.6.4.3 as well as Modi and Elliott (2006b) and Sickler and Elliott (2005).

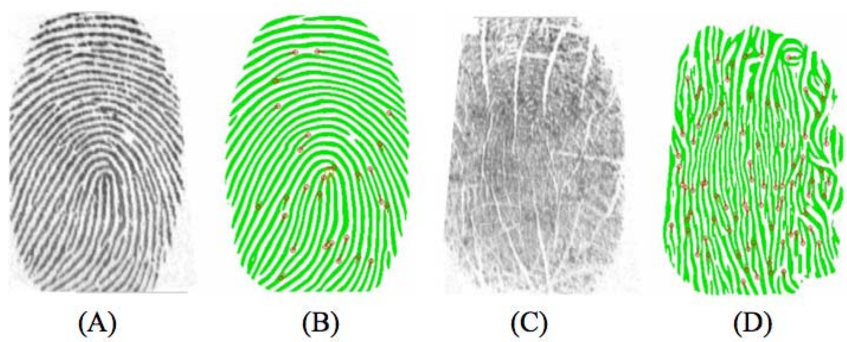


Figure 25 Raw and processed fingerprint images of a 22 year old (A & B) versus an 88 year old (C & D) (Sickler & Elliott, 2005).

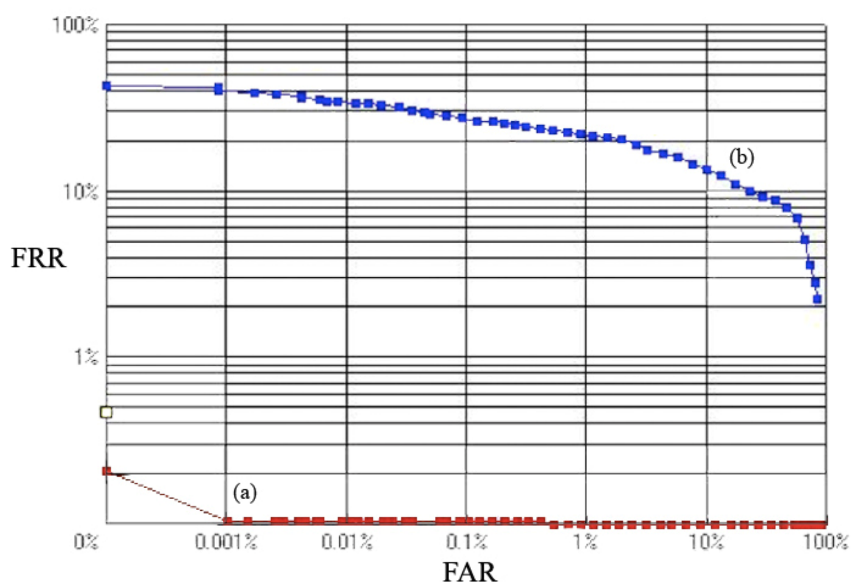


Figure 26 ROCs comparing performance of young and elderly fingerprints. Line (a) shows the 18-25-year-old population; line (b) shows the 62 and older population. Note that line (b) is shifted up and to the right, indicating poorer performance of the algorithm on that age group, compared to the algorithm's performance on the age group represented by line (a) (Modi & Elliott, 2006b).

Figure 27 Image of a low quality fingerprint (left) and image of a good quality fingerprint (right) (Elliott, Kukula, & Modi, 2007).

2.6.3.1.4. Environmental factors affecting biometric system performance

Environment and physical design vary over time, by application, and by implementation. For example, the U.S. Visitor and Immigrant Status Indicator Technology (US-VISIT) program utilizes face and fingerprint systems in multiple locations, namely all major U.S. airports, seaports, and border crossing immigration posts. Concentrating on the face component of this multimodal system, the positioning of the sensor (that is, its orientation or accessibility relative to the individual) and its surrounding environment can have a significant impact on the system's performance. Continuing the US-VISIT example, many airports in the United States were designed well before biometric systems were implemented in them, thus the environmental conditions, i.e. illumination levels, direction of the light, camera angle, and background are different in each location, which can have serious implications on system performance when images from different locations (airports) are compared and analyzed. Figure 28 provides examples of some of the potential variations that can cause problems with face recognition systems.

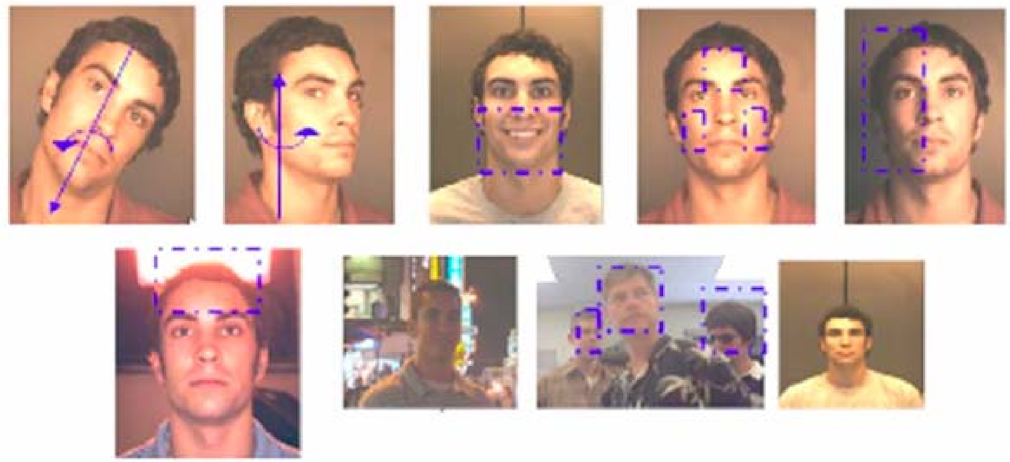


Figure 28 Examples of variations in facial images that cause problems with facial recognition (Elliott, Sickler, Kukula, & Modi, 2005).

Changes in illumination have historically been problematic for face recognition as discussed in Kukula and Elliott (2003), although emerging face recognition technologies such as near infrared and three-dimensional face systems have shown some resistance to illumination changes. Kukula and Elliott (2004) discusses the performance improvements of a three-dimensional face system under different illumination conditions. Figure 29 shows multiple examples of illumination levels and light directions which were used in Kukula and Elliott (2004). While these images were collected under ideal conditions in a laboratory environment, one can imagine the effects of that these different illumination conditions and directions can have on a system.

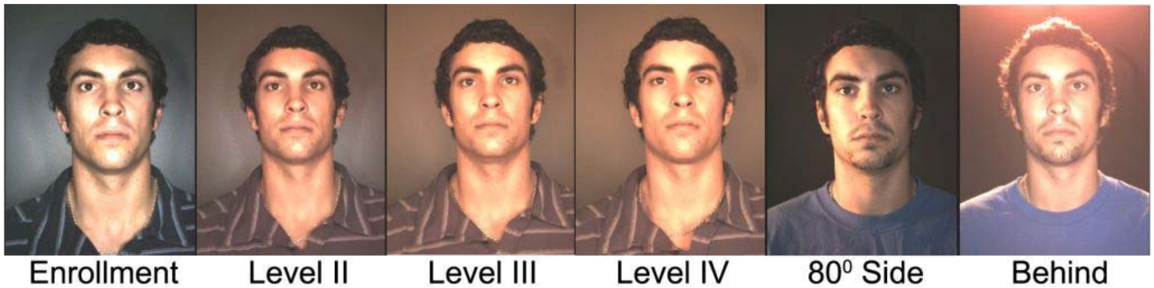


Figure 29 Six light levels and directions used for the 3D face evaluation (Elliott, Kukula, & Modi, 2007).

Because these four situations are not as uncommon as might be presumed, research must be undertaken to assess the impact of such problematic or difficult to collect samples on biometric system performance in general and on Human Biometric Sensor Interaction (HBSI) in particular.

2.6.3.1.5. Common Design Concerns

Biometric systems are heavily dependent upon the sensor to acquire the sample, segment it, and extract features from samples in order for the matcher to determine the correct response. By observing how users interact with biometric sensors, several design issues are apparent but could be resolved by integrating knowledge of industrial design, ergonomics and human factors, and usability. Rubin (1994) discusses five reasons why products and systems are difficult to use. The main problem is that the emphasis and focus has been on the machine/system and not on the end user during development. Common design misconceptions are:

- Humans are flexible and will adjust to a product or device;
- Engineers work well with technology but not with people;

- Engineers are hired to solve technology problems and not people skills; and
- Designers create products for users like themselves in terms of both usage and level of knowledge (Rubin, 1994).

These factors are true within the context of the biometric sensor. Humans will adapt to the sensor, as shown in Figure 24's examples of a hand geometry sensor and users' rotation of the hands. Many times, sensors and the form factors that surround the sensors are not tested on sufficiently large numbers of the general populations, namely due to the cost of doing so. Moreover, the biometric community may test the algorithms exhaustively off-line, using pre-collected images, but lapse on collecting images with a new sensor to examine how the user interacts with the device.

As technology becomes more pervasive, the target audience continually changes, causing design techniques, such as machine- or system- orientated approaches that focus on individuals like the designer, which are now outdated. Some organizations treat ergonomics and system design as common sense, thus as a lower priority than design of an algorithm. Lastly, design typically involves specialized teams and/or approaches for product and overall system development, but do not integrate well with each other, resulting in independent "parts" that do not function soundly as an integrated "product".

Investigation of how the user interacts with the device and development of system functionality are typically conducted separately. The skill sets and individuals required to perform these tasks are different (i.e., the test group typically sends data back to the client on a beta or production unit). Many times, problems inherent to the design of the form factor are blamed on the engineered sensor. This points to the need for research that examines how technology is intended to function in the field and how users actually use it (specifically, the interaction between humans and biometric sensors), as opposed to the traditional focus on functionality of the technology. According to Smith (2003), some members of the Human-Computer Interaction (HCI) community believe that interfaces of security systems do not reflect good thinking in terms of creating a system that is easy to use, while maintaining an acceptable level of security (p. 75). Moreover, according to Adams and Sasse (1999), security systems are one of the last areas to embrace user-centered design and training as essential. This is also true for biometrics as Coventry, De Angeli, and Johnson (2003b) stated the Human Computer Interaction (HCI) community has had limited involvement in the design or evaluation of biometric systems. Before further discussing human factors and ergonomic issues, the remaining components of the biometric model will be discussed.

2.6.4. Signal Processing

Next, the biometric system sends what the biometric model refers to as the sample on to the next silo – signal processing, which consists of three sub-processes: segmentation, feature extraction, and a quality control component. From quality control, three processes could follow: a subsequent presentation to the sensor if the quality did not meet the system criteria, which is known as a

Failure to Acquire (FTA), template creation for an enrollment process, or matching if the user is attempting identification or verification within the biometric system.

2.6.4.1. Segmentation

Segmentation is the first biometric signal processing sub-process and is responsible for determining if the acquired biometric sample consists of biometric characteristics, noise, or other features that are not of interest to the system. This task is completed using signal-to-noise ratios and analyses. Furthermore, if the segmentation algorithm determines that the sample does not contain the proper features, the system returns will return an FTA, meaning the user will have to perform a subsequent presentation to the sensor.

2.6.4.2. Feature Extraction

Once the segmentation sub-process determines the sample is, in fact, the proper biometric features of interest, the feature extraction sub-process processes the sample and extracts features of interest that can be used by either the template creation process or the matching algorithm. Extracted features for fingerprints include ridge presence, minutiae points, deltas, cores, and ridge patterns, to name a few. Again, if feature extraction fails, an FTA occurs and the user must present their biometric characteristics again to the sensor.

2.6.4.3. Image Quality

Once features are extracted, the next sub-process is image quality, where the features must meet or exceed a certain threshold of quality to continue through the system. If the quality of the features does not meet the threshold, an FTA occurs and the user is asked to present their biometric characteristics to the sensor again. Furthermore, it is well documented in the literature that image quality effects the biometric matching algorithm (Jain, Chen, & Dass, 2005; Modi & Elliott, 2006b; Tabassi & Wilson, 2005; Yao, Pankanti, & Haas, 2004).

Yao, Pankanti, and Haas (2004) state that “in a deployed system, the poor acquisition of samples perhaps constitutes the single most important reason for high false reject/accept rates” (p. 55). Yao, et al. (2004) state there are two solutions to reducing poor images. First, one can model and weight all adverse situations for the feature extraction and matching system. Second, which relates to this research, “one can try to dynamically and interactively obtain a desirable input sample” (Yao, Pankanti, & Haas, 2004, p. 55). Yao, et al. (2004) further narrows precise fingerprint image acquisition and image quality to contact problems, which can be decomposed into three main groups:

- Inconsistent contact
- Non-uniform contact
- Irreproducible contact (p. 56).

Moreover, most errors are due to inconsistent and non-uniform contact, therefore will be focused on in the following sections.

2.6.4.3.1. Inconsistent contact

As mentioned above, image quality affects biometric matching performance. Inconsistent contact is a significant problem for matching because it is known to decrease the similarity between fingerprints from the same person (Yao, Pankanti, & Haas, 2004). Yao, Pankanti, and Haas (2004) suggest two reasons for inconsistent contact, which both deal with the presentation to the sensor: presentation of differently distorted fingerprints and presentation of different portions of the finger to the sensor. Factors such as swiping speed, and pressure (force) are causes of the first item. While Levine et al. (2000) were awarded a patent to detect distortion due to pressure, it remains a factor in the biometrics community. Specifically, Kang, Lee, Kim, Shin, and Kim (2003) examined finger force and indicated force does impact quality, but did not specify quantitative measures, and classified force in three levels: low (softly pressing), middle (normally pressing), and high (strongly pressing).

Kukula, Elliott, Kim, and San Martin (2007) followed on the previous research of Kang, et al. (2003) and quantitatively examined the impact of the amount of force an individual applies to a large-area optical fingerprint sensor has on the image quality. Two experiments were performed with a CrossMatch Verifier™ 300 LC single optical fingerprint capture device. Experiment 1 consisted of 29 participants between the age of 18 and 25, which took place in October of 2006. Experiment 2 consisted of 43 participants aged between 18-25 years old and took place in January of 2007. Both experiments used the right index finger, with two exception cases, due to scarring or other irregularities, thus one used the right middle, and the other the left index finger. Four force levels were used in experiment one, while five were used in experiment two, that primarily investigated the three to nine Newton range (Figure 30). Results from the first experiment indicated that there was no incremental benefit in terms of image quality when using more than 9N of force when interacting with an optical fingerprint sensor. The second experiment investigated the 3-9N interval with results indicating that the optimal image quality is arrived between a force level is 5-7N, as shown in the frequency plots of the image quality scores by force level (Figure 31).

Experiment 1				Experiment 2				
								
3N Force Quality 53	9N Force Quality 60	15N Force Quality 74	21N Force Quality 84	3N Force Quality 3	5N Force Quality 87	7N Force Quality 91	9N Force Quality 88	11N Force Quality 90

Figure 30 Finger force levels and resulting images with image quality scores (Kukula, Elliott, Kim, & San Martin, 2007).

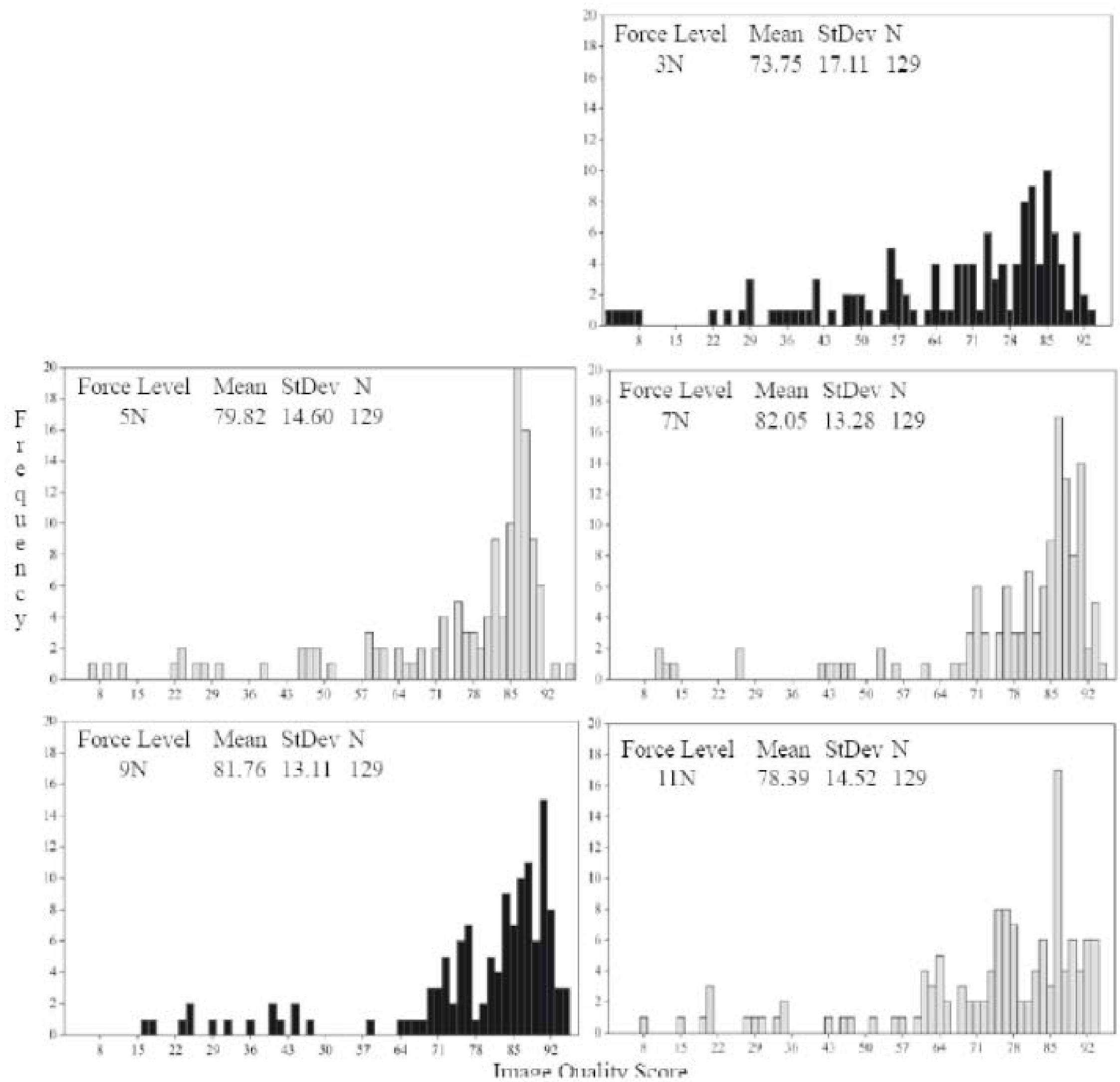


Figure 31 Experiment two frequency plot of quality scores by force level (Kukula, Elliott, Kim, & San Martin, 2007).

Swipe-based fingerprint sensors add another dimension to inconsistent contact, due to the individual being required to swipe their finger across the sensor. Comparing the fingerprint images in Figure 32, one can see there is limited variability in the image size for those captured with the large area optical sensor. However, for the images captured with the swipe-based fingerprint sensor, there is variability both within subject and across subject, which will pose problems for the image quality and matching algorithms, thus impact the overall performance of the biometric system.

Figure 32 Images captured with different type and size sensors.

This difference between sensor technologies is further illustrated in an unpublished report by Kukula, Elliott, Wolleschensky, Parsons, & Whitaker (2007) which revealed that the variability in the mean number of enrollment attempts is lower with the small-area sensor than swipe-based sensor. While different acquisition and extraction algorithms were used for each of the sensors, one can see from Figure 33 the consistency for the small-area sensor and the extreme variability with the swipe-based sensor.

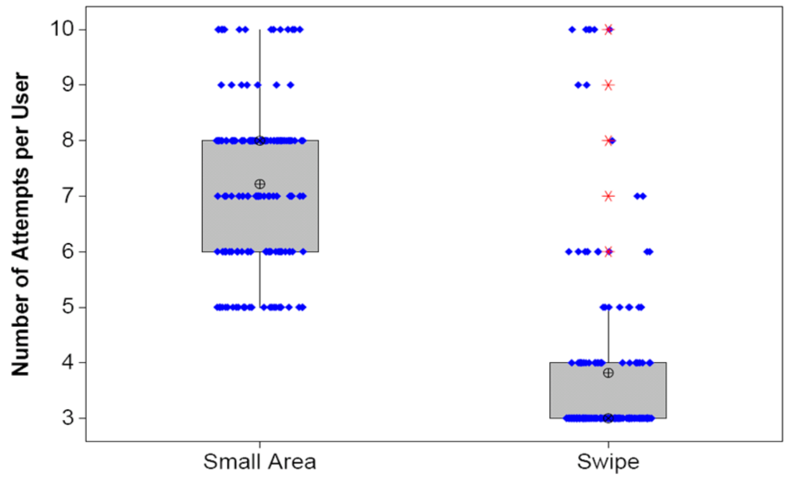


Figure 33 Number of attempts to enroll per user with two different sensor technologies (Kukula, Elliott, Wolleschensky, Parsons, & Whitaker, 2007).

Finally, methods to evaluate inconsistent contact have been examined in the literature. Lim, Jiang, and Yau (2002) evaluated inconsistent contact using three metrics. First, the strength and direction of the ridge orientation was assessed to determine the contrast of the fingerprint image. Secondly, an examination of the structure between ridges and valleys was conducted using the gray-level profile of the fingerprint image. Lastly, Lim, Jiang, and Yau (2002) analyzed the change in ridge direction. This research also utilizes a number of metrics to examine consistency of contact with the biometric sensor and will be discussed in section 2.8.4.2.1.

2.6.4.3.2. Non-uniform Contact

There are many factors reported in the literature that affect fingerprint image quality, such as: age, gender, ethnicity, moisture content of the skin, diseases of the skin, dirt, humidity, and temperature. These factors are just a few that contribute to non-uniform and non-ideal contact situation (Elliott, Kukula, & Sickler, 2004; Jain, Chen, & Dass, 2005; Kang, Lee, Kim, Shin, & Kim, 2003; Maio, Maltoni, Cappelli, Wayman, & Jain, 2000; Modi & Elliott, 2006b; Tabassi & Wilson, 2005; Wayman, 2000; Yao, Pankanti, & Haas, 2004; M. Young & Elliott, 2007). While these factors cause dry looking or smudgy prints, this can only be minimally improved by altering the design of the form factor. Rather this is a problem that the signal processing and matching researchers need to focus on, thus is outside the scope of this study.

2.6.5. Storage

Storage of individuals' biometric information in the form of a sample or samples is typically referred to as a template. If users are not stored in the database, they undergo the process of enrollment. During enrollment, users present their characteristics to the sensor and the system performs the operations discussed up to this point. However, the sample, which may consist of one or more images, features, or data will be stored in the database as a template. This template is what the matching algorithm uses for subsequent identification or verification attempts. If the samples do not meet the criteria to create the biometric template, a Failure to Enroll (FTE) occurs. In cases where this happens, the individual is asked to present their biometric characteristics to the sensor again.

2.6.6. Matching

If the individual previously enrolled in the biometric system, the extracted features that exceeded the quality metric will be compared to the template using a matching algorithm. For fingerprint recognition, there are two main matching algorithms: minutiae and pattern based. Since there is inherent variability with a human interacting with a biometric sensor, meaning that no two interactions will be the same, the resulting features will never exactly match to the template stored in the database. Refer to section 2.6.3.1.3 for more information on variability in biometric characteristics. Since an exact match is highly unlikely, a matching score, which is also referred to as a similarity score, is typically produced by the matching algorithm, which indicates a likelihood of the match. Typically, fingerprint-matching algorithms indicate strong matches with higher scores, with lower scores representing lower matches, but this does not hold for all systems. In addition, there is not one common methodology for computing the score, and is thus algorithm dependent. Once the score is generated, it is sent to the decision silo.

2.6.7. Decision

Once the decision silo receives the similarity score from the matching algorithm, the decision module compares the similarity score to a system-defined threshold. If the similarity score meets or exceeds the criteria of the threshold and the individual is in fact the correct individual that is claiming to be enrolled in the database, the individual presenting the sample is “matched’ to the template stored in the database, also known as verified. However, there are systems that function where individuals do not have to make an explicit claim to an identity. In such cases, the similarity score is used to determine if the user is a candidate, by comparing against the threshold. If the individual appears on the returned list of candidates, the system may require further comparison or ranking. If the correct individual is included in the candidate list, and is matched, they are referred to as identified. The two cases presented above are called verification and identification, respectively. Verification systems match individuals based on a one-to-one basis. Users explicitly claim to be enrolled in the database and provide either knowledge or token-based information to claim that they are indeed in the database. Contrary to this, identification systems require no claim of identity. Rather, biometric characteristics are presented to the sensor and the system searches either the entire database (one-to-many) or a partial database (one-to-few) for possible matches.

In the case where the similarity score does not meet the threshold criteria, the claim is rejected for verification, or not matched for identification. In previous sections, we discussed FTA and FTE. However, the decision module can have errors relating to it as well, as an individual may be falsely accepted or rejected. These error rates are discussed in section 2.8.4.2.2. These error rates are variable and are dependent upon the threshold level. There are multiple reasons for individuals being falsely accepted or rejected, but a majority of errors are due to sample variability, which may be due to the presentation to the sensor, environmental factors, or changes to the biometric characteristics of interest.

2.6.8. Framing Research within the Biometric Model

A large number of research papers and books have focused on biometric systems and technologies. In addition, most of the research in biometrics has investigated sensor technologies, extraction algorithms, image quality algorithms, and matching algorithms. However, there has been limited research in how the user interacts with and presents to the biometric sensor and attributes the subsequent errors or failures to the actions or behaviors of the user separate from the biometric system. These two areas are represented in Figure 34, which segregates the general biometric model into two components: data capture (left and squared) and the remaining 4 silos: signal processing, data storage, matching, and decision (right and covered). This dissertation is primarily concerned with the data capture portion of the model, as it is where the human interacts with the sensor.

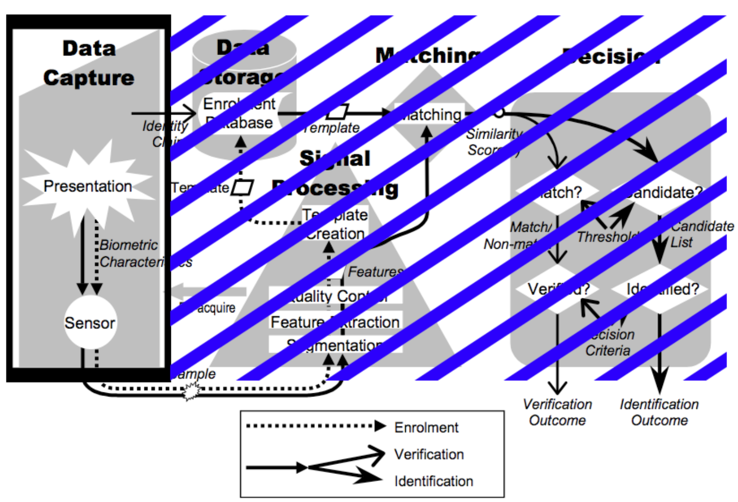


Figure 34 Segregated general biometric model indicating the focus of the dissertation (International Standards Organization, 2006a).

2.7. Human Factors and Ergonomics

2.7.1. Anthropometry

Anthropometry derives from the Greek words "*anthropos*," meaning man, and "*metron*," meaning measure. It is the empirical science that evaluates body measurements; such as size, strength, shape, mobility, flexibility, and working capacity, as well as defines physical dimensions and characteristics of a person such as: weights (masses), volumes, centers of gravity, and body segments (Bhattacharya & McGlothlin, 1996; Pheasant, 2006; Tayyari & Smith, 2003). Albrecht Dürer, one of Leonardo da Vinci's young contemporaries, is regarded as the pioneer of modern scientific anthropometry. Dürer wrote Four Books of Human Proportion, which attempted to categorize the diversity of human physical types based on systematic observations and measurement of large numbers of people (Pheasant, 2006). Moreover, Alphonse Bertillon created an identification system based upon anthropometric measurements, which were used to identify and classify criminals. The measurements he used are shown in Figure 35.

Figure 35 Bertillon's anthropometric identification system (U.S. National Library of Medicine, 2006).

According to Pheasant (2006) anthropometry attempts to match two things: the physical form and dimensions of the product to the user and the physical demands of the working task to the capacities of the workforce (p. 7).

Once the designer or engineer understands the demands and capabilities of the user population and evaluation of the interaction of the products or system and human must be completed. This is known as ergonomics and will be discussed after anthropometric measurements and the relation to work performance are discussed.

2.7.1.1. Hand Size and Performance

Salvendy (1971) investigated the effect of hand size and other anthropometric measurements have on assembly performance. Three tasks were performed that involved repetitive psychomotor tasks in the electronics, electro-mechanical, and confectionary industries. In particular, the test sought information to determine if performing manual repetitive tasks have an effect on production performance or tests of manual dexterity. This study involved one hundred eighty one right-handed females that were either industrial operators performing the tasks (N=127) or being trained to perform the tasks (N=54). Twelve anthropometric measurements were collected and are shown in Figure 36.

Results revealed that individual anthropometric data had a non-significant effect on the performance of the psychomotor tests – One-Hole Test, Purdue Pegboard, and the production performance of the workers in the three tasks (Salvendy, 1971). However, when age, personality scores, intelligence, and dexterity tests were covaried as influencing factors of the anthropometric data, a significant multiple correlation coefficient was yielded with production performance (Salvendy, 1971). Moreover, Salvendy (1971) states that "11 out of 12 anthropometric correlation coefficients with the production performance are positive indicating that big hands go with high performance" (p. 36).

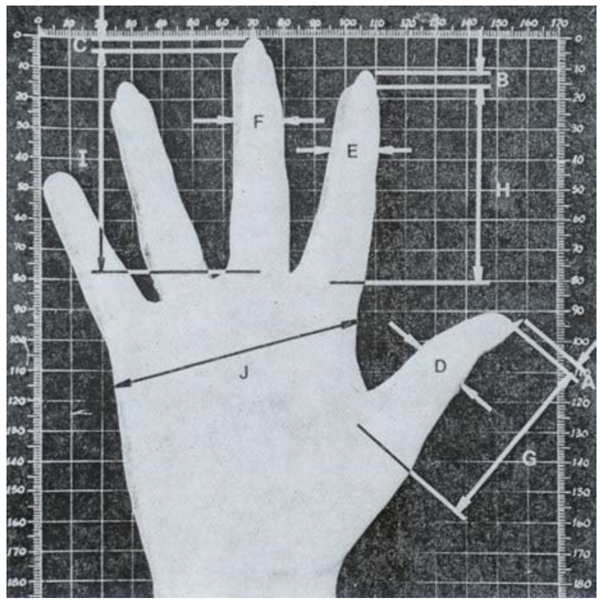


Figure 36 Twelve anthropometric measurements used in Salvendy (1971).

2.7.1.2. Finger Selection and Biometric Performance

Although the biometric community has not gathered anthropometric data explicitly in prior studies, one can deduce information regarding anthropometric data, specifically with the fingers. In Wayman (2000), fingerprint classification statistics were released based on an unpublished report using twenty-two million human-classified fingerprint records from the FBI, which is shown in Table 5. This shows the dependence of finger classification on the finger itself. More importantly, Wayman (2000) discussed the matching performance of the digits of each hand. Specifically, as one moves from the thumbs to the ring fingers, there is an increase in the number of matching errors (Figure 37). The dataset included fingerprints from over 510 Philippine adults, 55% of which were female, which were collected with an Identicator DF-90 "flat" scanner.

Table 5 Single finger classification statistics on 22M human-classified fingerprint records (Torpey, 1995).

		Pattern Type						
Hand	Finger	Arch	Tented Arch	Right Loop	Left Loop	Whorl	Scar	Amp
Right	Thumb	3.0%	0.4%	51.3%	0.5%	44.8%	0.0%	0.1%
	Index	6.1%	7.7%	36.4%	17.0%	32.5%	0.2%	0.2%
	Middle	4.4%	3.2%	73.4%	1.5%	17.2%	0.1%	0.2%
	Ring	1.2%	1.0%	51.2%	1.1%	45.2%	0.1%	0.1%
	Little	0.9%	0.7%	83.0%	0.3%	15.0%	0.1%	0.1%
Left	Thumb	*5.2%*	*0.6%*	*0.6%*	*58.4%*	*35.0%*	*0.0%*	*0.1%*
	Index	*6.3%*	*8.0%*	*16.5%*	*39.0%*	*29.9%*	*0.1%*	*0.2%*
	Middle	*5.9%*	*4.5%*	*1.7%*	*70.3%*	*17.3%*	*0.1%*	*0.2%*
	Ring	*1.8%*	*1.5%*	*0.5%*	*61.5%*	*34.6%*	*0.1%*	*0.2%*
	Little	*1.2%*	*1.1%*	*0.1%*	*86.1%*	*11.3%*	*0.1%*	*0.1%*
Average		*3.6%*	*2.9%*	*31.5%*	*33.6%*	*28.3%*	*0.1%*	*0.2%*

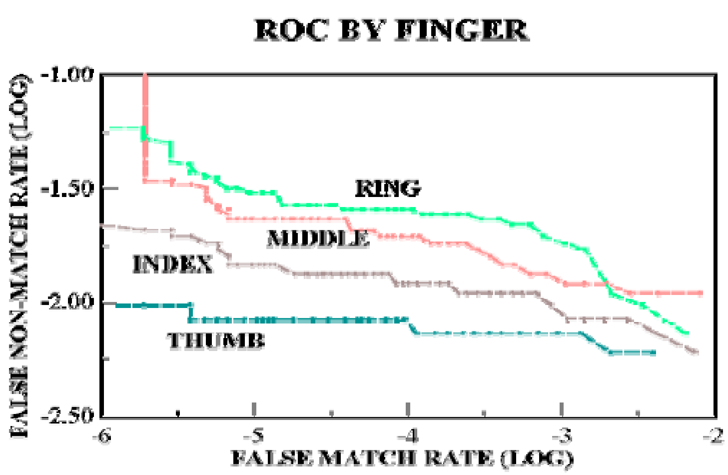


Figure 37 Left and right hand ROC curves by finger (Wayman, 2000).

Young and Elliott (2007) conducted a similar test on a small scale sample size of fifty participants, of which 66% were males, with age range of 19 to 65 years old, with a mean of 32.87. The sensor used for capturing fingerprints was the Identix, Inc. DFR®-2080U2 Single Finger Reader (Figure 43 right), which operates at 500 dpi. Fingerprint matching performance was similar to the results of Wayman (2000), with the only difference being the little fingers were tested instead of thumbs. However, the results were the same; as the acquisition finger changed from the index finger outward, the number of errors increased, which is shown in Figure 38.

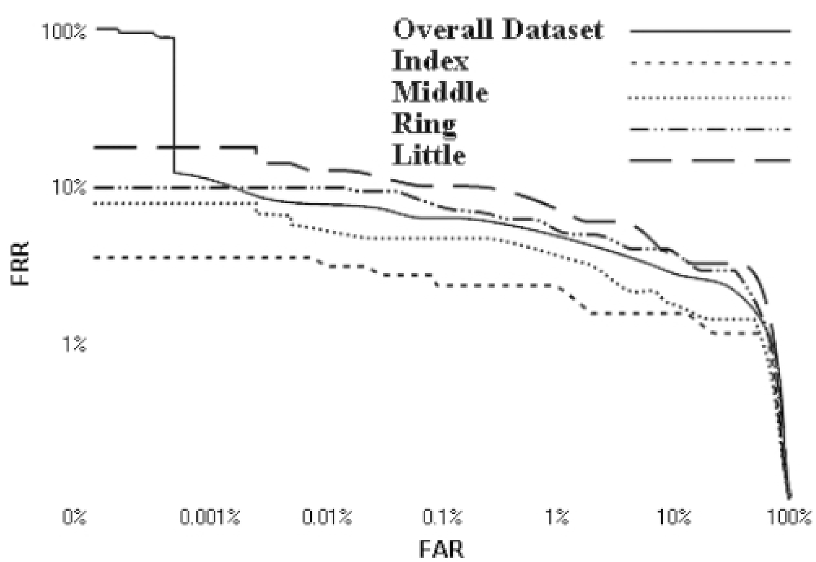


Figure 38 Left and right hand ROC curves by finger (M. Young & Elliott, 2007).

2.7.2. Ergonomics and User-Centered Design

The term ergonomics was conceived in 1949 by Professor Hywell Murrell in a meeting that created a society for "the study of human beings in their working environment" in London (Pheasant, 2006). Ergonomics derives from the Greek words "*ergon*," or work, and "*nomos*," meaning laws. While the term work has been traditionally associated with occupation, a broader sense of the term can be applied to any unplanned activity requiring skill or effort. In 2000, the International Ergonomics Association [IEA] (2006) defined ergonomics or human factors as:

> The scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data and methods to design in order to optimize human well-being and overall system performance.

In design, ergonomics attempts to achieve an optimal relationship between humans and machines in a particular environment. The goal of ergonomics, according to Tayyari & Smith (2003), is to "fit (adapt) work to individuals, as opposed to fitting individuals to the work" (p. 1). Figure 39a presents the model proposed by Tayyari & Smith (2003) to show where ergonomics fits in the human-machine interaction. Pheasant (2006) further summarized ergonomic design by the principle of user-centered design. This principle states "If an object, a system, or environment is intended for human use, then its design should be based upon the physical and mental characteristics of its human users" (p. 5).

Moreover Woodson (1982) states the design should allow users to complete the desired functions and tasks with minimal stress and maximum efficiency. Therefore, the object of ergonomics and user-centered design is to achieve the best possible match between the product and users in the context of the task to be performed, which Figure 39a represents (Pheasant, 2006).

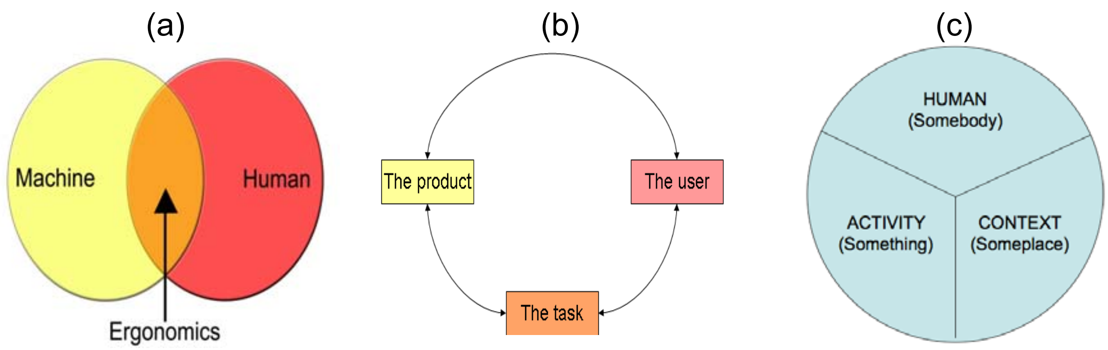


Figure 39 (a) The fit of ergonomics in the human and machine interaction (Tayyari & Smith, 2003), (b) the user-centered design approach (Pheasant, 2006), and (c) Bailey's Human Performance Model (Bailey, 1982).

Chignell and Hancock (1992) referred to this as the "design triad", which consists of three primary relationships. The first is the user-task relationship, which is much like task analysis and answers the following questions: "What is the task?" and "How is it carried out by the user?" The second relationship is user-artifact, which is the relationship between the user and the system and lies at the heart of ergonomics (Figure 39b) (Chignell & Hancock, 1992). Lastly, the artifact-task relationship represents the methodology for using the system to perform the task, which is also known as methods improvement (Chignell & Hancock, 1992). Yet a third model describes a similar set of three components to consider when examining a human-performance situation: 1) the human, 2) the context, and 3) the activity, which form Bailey's Human Performance Model (Figure 39c). The importance of this generic model is to consider all three components – they all affect how humans perform.

Traditionally engineers, designers, and programmers have placed the greatest amount of emphasis on the activity, some emphasis on the context and human, but have neglected the relationship between the components (Rubin, 1994). In order to see if the end product is useful, effective, efficient, and satisfactory to the users, which are common metrics for usability, the relationship between the three components must be further evaluated. Specifically, understanding of the user demands and capabilities, the system design that fits these, and the desired end application.

2.7.3. Usability

Good design must address not only ergonomics and anthropometry, but also usability. Usability has been defined by the International Organization for Standardization (ISO) (1998) as the extent to which a product can be used by specified users to achieve specified goals (p. 2). Usability testing employs techniques to collect empirical data during the observation of users using the product for a specific task in order to rectify usability deficiencies of a product (Rubin, 1994). The ISO document 9241-11 (1998) discusses three factors that compose usability: effectiveness, efficiency, and satisfaction. Almost 10 years earlier, Booth (1989) identified four factors, some of these overlap with the later ISO 9241-11 document, that operationally define usability: usefulness, effectiveness, learnability, and likeability. Table 6 organizes the factors of usability by factor, description, and a possible measurement metric. The IEEE Standard Computer Dictionary (1990) further describes usability as the “ease with which a user can learn to operate, prepare inputs for, and interpret outputs of a system or component”.

Table 6 Common Usability Factors, Descriptions, and Metrics (Booth, 1989; International Organization for Standardization, 1998).

Usability Factor	Description	Metric	Metrics found in the literature
Usefulness	An assessment of the user’s motivation for using a product. Most likely to be overlooked during experiments and studies in the lab (Rubin, 1994).	User Motivation	User satisfaction questionnaires (Kirakowski, 2007; Lewis, 1993)
Effectiveness	Accuracy and completeness that users will achieve specified goals. Provide utility and functionality that is highly valued by the user (Gould & Lewis, 1985).	Quantitative metrics, such as speed of use or error rates.	Counting of errors: ▪ Incorrect/ forgetting ▪ Skipping a step ▪ Accepting a wrong answer (J. Young, 2005) Acceptability/ Conformance taxonomy (Micheals, Stanton, Theofanos, & Orandi, 2006) Number of participants who were unable to complete the task (Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007)

			Number of errors incurred by the participants who successfully completed the task (Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007)
Efficiency, Learnability	Resources expended in relation to the accuracy and completeness of the goals. Ability to operate the system to some defined level of competence after a period of training or ability to relearn after a period of inactivity.	Activity time, number of errors, pre- and post-testing.	▪ Time to complete each session (J. Young, 2005) ▪ Time to complete each task (Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007; J. Young, 2005)
Satisfaction, Attitude (Likeability)	Freedom from discomfort. User's perceptions, feelings, and opinions of the product.	Surveys, ranking of products.	▪ 5 point Likert scale usability Survey (J. Young, 2005, p. 12) ▪ 5 point Likert scale satisfaction survey (Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007, pp. 40-42)

2.7.3.1. User-Centered Design

One methodology that supplements the factors of usability is User-Centered Design (UCD). UCD are processes that provide engineers a method to design from the human-out. Gould and Lewis (1985) named three principles of a user centered design:

- Focus early on users and tasks and have contact between designers and users throughout the development cycle.
- Collect behavioral measurements of the product-user interaction, the ease of learning, and the ease of use through prototype testing.
- Perform iterative design and testing.

Other techniques, methods, and practices of UCD besides usability testing and audits include: participatory design, focus group research, surveys, design or structured walk-throughs, paper and pencil evaluations, expert evaluations, field studies, and follow-up studies (Rubin, 1994).

2.7.3.2. Issues in the Usability Literature

Upon reviewing a number of papers from the usability community, one can see they suffer from too many metrics that often has a baseline measurement that is hard to determine for comparison purposes. In addition, the number of subjects the usability studies have used as evaluators or participants is problematic. For example, Andre, Hartson, and Williges (2003) proposed an evaluation method and tested it using a class of nineteen computer science or engineering students, who were not in the usability field and only received approximately one to two hours of training on the particular method.

The other main limitation is sample size, which is also an issue for the biometrics community. Moreover, the question: “How much testing is enough?” plagues most researchers in all fields. While the biometrics community has adopted a two hundred and fifty person test as the industry standard for large-scale evaluations, most ergonomics and usability studies are limited to five to 30 participants, which if usability studies are adopted in the biometrics community, would be dismissed by many if presented with a study of such magnitude. While the biometrics community believes in large-scale evaluations for commercial products, many research and academic studies face the same challenges of small or uneven sample sizes. For example, a study performed by Andre, Hartson, and Williges (2003) that compared three Usability Evaluation Methods (UEM) revealed that fewer than twenty users would have been needed to detect most of the real problems found in the address book that was used for testing, which is shown in Figure 40. Furthermore, Table 7 lists some of the more referenced literature in usability, the methods used, and number of subjects tested, illustrating the problem discussed above.

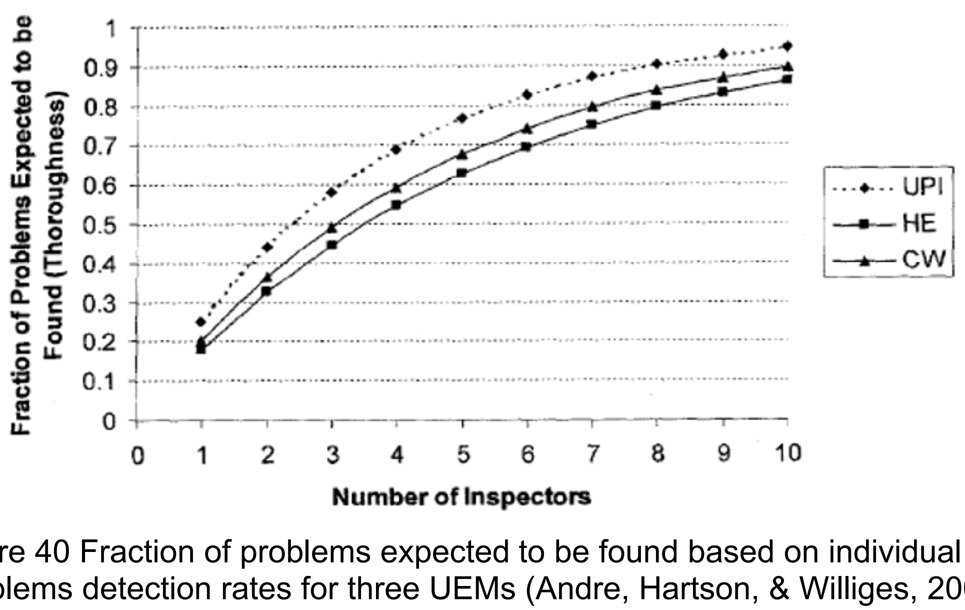


Figure 40 Fraction of problems expected to be found based on individual real problems detection rates for three UEMs (Andre, Hartson, & Williges, 2003).

Table 7 Usability literature: methods and subjects tested.

Study	Method(s)	Subjects
Bastien and Scapin (1995)	Ergonomic Criteria	10
	No Method	10
Bastien, Scapin, and Leulier (1996)	Ergonomic Criteria	6
	ISO	5
	No Method	6
Beer, Anodenko, and Sears (1997)	Cognitive Walkthrough	6
	Think Aloud	6
Cuomo and Bowen (1992; , 1994)	Heuristic Evaluation	2
	Cognitive Walkthrough	2
	Guidelines Review	1
Desurvire, Kondziela, and Atwood (1992)	Heuristic Evaluation	3
Desurvire and Thomas (1993)	Cognitive Walkthrough	3
	Programmed Amplification of Valuable Experts	3
	Usability Laboratory Test	18
Doubleday, Ryan, Springett, and Sutcliffe (1997)	Heuristic Evaluation	5
	Usability Laboratory Test	20
Dutt, Johnson, and Johnson (1994)	Heuristic Evaluation	3
	Cognitive Walkthrough	3
Jeffries, Miller, Wharton, and Uyeda (1991)	Heuristic Evaluation	4
	Cognitive Walkthrough	3
	Guidelines Review	3
	Usability Laboratory Test	6
John and Marks (1997)	Claims analysis	1
	Cognitive Walkthrough	1
	GOMS	1
	Heuristic Evaluation	1
	User action notation	1
	Specifications	1
John and Mashyna (1997)	Cognitive Walkthrough	1
	Usability Laboratory Test	4
Karat, Campbell, and Fiegel (1992)	Individual walk through	6
	Team walk through	6
	Usability Laboratory Test	6
Nielsen and Molich (1990)	Heuristic evaluation	34, 77
Nielsen (1990)	Think aloud	36
Nielsen (1992)	Heuristic Evaluation	31, 19, 14
Sears (1997)	Heuristic Evaluation	6
	Cognitive Walkthrough	7
	Heuristic Walkthrough	7

Virzi, Sorce, and Herbert (1993)	Heuristic Evaluation	6
	Think aloud	10
	Usability Laboratory Test	10
Virzi (1990)	Think aloud	20
Virzi (1992)	Think aloud	12
Fu, Salvendy, and Turley (2002)	Heuristic Evaluation	6
	Usability Testing Methods	6

2.7.4. Related Ergonomic, Usability, and Human-Computer Interaction Literature

Some research analogous to HBSI exists in the ergonomic literature, usually from the study of computer keyboard typing. These studies examine ergonomic issues concerning the upper extremities, including the hands, wrists, and fingers. These studies are important to biometric system designers, as commercially available fingerprint and hand geometry systems require some sort of interaction or contact with a sensor or device using the same upper extremities. Typically, sensors that use these upper extremities are becoming increasingly popular. One can argue that one of the most influential inventions of the twentieth century with regards to information technology was the computer mouse. The invention of the mouse in 1963 changed the way users interacted with computer interfaces; decreasing the level of complexity required to interact and manipulate items on a computer visual display terminal. While other devices were crafted, comparative testing undertaken by NASA in the 1960s between light pens, cursor keys, joysticks, trackballs, revealed that mouse designed by Engelbart and English resulted in their device outperforming the other devices due to its ease of use (Moggridge, 2007). Figure 41 shows early designs of the mouse. Stu Card, one of the pioneers of the mouse, recalls that Fitts' Law was used to test the movement of the hand with and without the mouse device (Moggridge, 2007). Observations and tests showed that the slope of that curve was about 10 bits per second, which was very similar to the measurements for just moving the hand alone without a device, revealing the limitation was not the mouse device, rather was the hand-eye coordination system of the user. Since the time to move the hand with and without the device was very similar English and Card concluded the design was nearly optimal.

Figure 41 First mouse design 1963-64 (left), first production mouse (3rd picture from left). Xerox mouse designs during the 1980s (3 images to the right in order of increasing radical design) (Moggridge, 2007).

Therefore, those working with examining the human-biometric sensor interaction can learn much from the early pioneers in HCI, especially from the development of the mouse, as it was a vital component of humans interacting with computers. Moreover, according to Greenberg and Chaffin (1977) by not taking human factors into consideration during design, common problems that often arise are: injuries, stressors on the body, pain, physical and mental fatigue, as well as an increased learning time, which can be seen in the following examples with hand geometry and fingerprint recognition devices.

In the case of hand geometry, the platen or acquisition surface is typically flat; depending on the height of the device, the extension/flexion angle of the distal wrist could potentially be uncomfortable to users. Figure 42 shows a hand geometry acquisition platen that forces users to flex their wrist. For fingerprint recognition, the interaction between the thumb and a fingerprint swipe sensor forces extensive ulnar deviation to the wrist (see Figure 43 left). The middle and right images in Figure 43 shows a capacitance and optical fingerprint sensor and the form factors. The three images in Figure 43 reveal three things. First, the small size of the capacitance sensor housing can result in users overextending their fingers to reach the device. Second, the height of the sensor, relative to the top of the table, could cause the other digits of the hand to collide with the table, causing discomfort. Compared to the capacitance sensor, the optical sensor is positioned well off of the table surface, allowing for clearance of the digits not interacting with the sensor. Third, the finger guide impression of the capacitance sensor accommodates larger fingers, but does not produce appropriate feedback for those with smaller fingers, allowing more variability to occur between placements over time. In a similar fashion, the plastic lip of the optical sensor is angled in such a way that those with smaller fingers try to align their finger with the lip and not the glass surface of the sensor, causing repeatability issues.

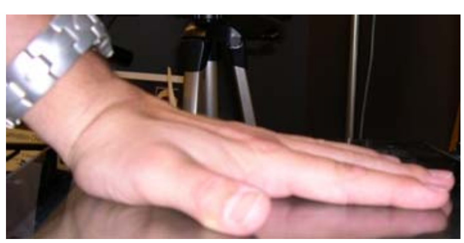


Figure 42 Image acquisition on a flat platen causing wrist extension.

Figure 43 Interaction between thumb and fingerprint swipe sensor produces ulnar deviation (left), Capacitance sensor (middle) and optical fingerprint sensor (right) with finger alignment and guidance impression (Kukula, Elliott, & Duffy, 2007).

2.7.4.1. Computer input device research

As the sensors in the figures above show, users of these devices may experience stressors on the body. These stressors could be exacerbated when individuals have tendonitis, tenosynovitis, arthritis, or any other MSDs that might impede their ability to efficiently use the biometric device. Armstrong (1986) noted that a deviated wrist posture on the flexion/extension plane is implicated in the etiology of diseases or abnormal physiological conditions of work-related musculoskeletal disorders of the wrist. Further research on the wrist revealed carpal tunnel pressure decreases as the wrist moves toward a neutral posture in the flexion and extension planes (Rempel, Kier, Smutz, & Hargens, 1997; Weiss, Bloom, & Rempel, 1992). Moreover, as the wrist moves from the neutral position in the positive direction, the force on the carpal bones and tendons increases (Armstrong & Chaffin, 1978a, , 1978b; Schoenmarklin & Marras, 1990).

A study by Rempel et al. (1997) measured carpal tunnel pressure at multiple wrist extensions and found that, at 15° wrist extension, carpal tunnel pressure was 18.55 mm Hg, which increased to 27.7 mm Hg at 30° with no fingertip loading. Under a fingertip loading of 6 Newtons (1.47 lb), comparable to typing on a keyboard, carpal tunnel pressure increased to 41.1 and 53.5 mm Hg, respectively, at 15° and 30° wrist extension angles. This reveals the second concern for biometric systems. The device orientation, wrist extension angles, and motion or orientation of the fingers may cause discomfort and pain, resulting in users not being able to use the device, individuals not being able to provide an acceptable sample or image to the system, or in the worst-case scenario, not being able to provide repeatable placements or images over time. The impact of non-repeatable placements or images is significant, as it challenges the algorithm and system to match samples or images from users with varying characteristics and attributes.

2.7.4.2. Human factors and usability studies in biometrics

At the time of writing, literature on the subject of ergonomics and usability in the biometrics community is limited. Coventry, De Angeli, and Johnson (2003a; , 2003b), Theofanos, Michaels, Scholtz, Morse, and May (2006), Theofanos, Orandi, Micheals, Stanton, and Zhang (2006), Theofanos, Stanton, Orandi, Micheals, and Zhang (2007), Young (2005) and Maple and Norrington (2006) have focused on biological biometrics, while Deane, Barrelle, Henderson, and Mahar (1995), Deane, Henderson, Mahar, and Saliba (1995), and Henderson, Mahar, Saliba, Deane, and Napier (1998) focused primarily with perceived acceptability of behavioral biometrics.

2.7.4.2.1. User perceptions and acceptability of biometrics

Deane, Barrelle, Henderson, and Mahar (1995) conducted a survey of perceived acceptability of biometric security systems using 76 test participants from the banking sector and university administration. The survey assessed the acceptability of seven biometric technologies (fingerprint, hand geometry, keystroke dynamics, retinal imaging, signature, voice verification, and pointing device verification) in relation to participants' present jobs and compared to traditional knowledge based systems, such as passwords. The results of the survey revealed that physiological biometrics — in this case finger, hand, and retina — were considered more acceptable than behavioral modalities — in this case, signature, voice, keystroke dynamics, and pointing device — with scores of 3.34 and 2.66, respectively, based on a five-point Likert scale, where 1 was "totally unacceptable" and 5 was "totally acceptable." Deane et al. (1995) also polled the acceptability level of passwords with the same five-point Likert scale, generating a result of 3.85. Paired *t*-tests revealed a significant difference between password acceptability and both physiological biometric acceptability, $t(64) = 2.75$, $p < 0.01$) and behavioral biometric acceptability, $t(62) = 7.73$, $p < 0.001$). Deane et al. (1995) also examined acceptability of biometric methods based on the sensitivity of information handled. This analysis revealed that, as the sensitivity of information increased, the acceptability of biometrics did as well for keystroke dynamics and fingerprint, while password acceptability decreased. Since this study was published in 1995, the way in which privacy and security of personal and company data are handled has drastically changed. The United

States has recently passed several regulations that require companies to take into account general concerns such as physical and logical security. Specifically, the Sarbanes-Oxley Act ("Sarbanes-Oxley Act of 2002", 2002) and the Food and Drug Administration’s 21 CFR Part 11 (1997) are two such regulations that require companies to apply specific controls or procedures to ensure authenticity, integrity, and auditability of electronic records (Modi & Elliott, 2006a).

2.7.4.2.2. Fingerprint swipe-sensor usability research

2.7.4.2.2.1. NCR

Coventry, De Angeli, and Johnson (2003a) examined fingerprint swipe sensors, but from the perspective of the relationship between image quality and user feedback. In order for Coventry et al. (2003a) to evaluate user support, three levels of instruction and feedback were used: Level 0 – no instruction and limited feedback, Level 1 – instruction and limited feedback, and Level 2 – full instruction and feedback. The results revealed that successful verification was not affected by the type of instruction and feedback received and that some individuals have problems that cannot be solved through instruction, training, or feedback. One possible explanation could be the design and placement of the sensor and/or the digit chosen for the attempt. It is also interesting to note that in Coventry et al. (2003a), participants chose which finger to use. The results revealed that, of 82 subjects, 64 chose their right index finger (78%), 16 used their right middle finger (20%), while 2 participants used their left middle finger.

2.7.4.2.2.2. Purdue

These results were similar to Kukula and Elliott (2006), which evaluated a capacitance swipe sensor embedded in a commercially available laptop computer. The purpose of the evaluation was to examine issues related to fingerprint acquisition of all 10 digits to evaluate the biometric-user interface in terms of biometric performance metrics, error rates, in particular the FTA and FTE rates. The study involved 88 participants, most of which were between the ages of 18 and 30. The research identified multiple factors warranting consideration when designing a biometric system in order to better understand why failures occur and how individuals react to systems. The results of this experiment revealed that the medial digits (thumb, pointer/index, and middle) had fewer acquisition problems than the lateral digits (ring and little fingers) of both hands, which can be attributed to a decrease in finger dexterity as one moves from the index to the little finger, which is shown in Table 8. Moreover, an examination of the left image in Figure 43 left, the ulnar deviation required for a user's thumb to interact with the sensor can be seen. Lastly, the finger error rate results are similar to the matching performance errors found in Wayman (2000) and Young and Elliott (2007) that were discussed in Section 2.7.1.2.

Table 8 Individual and combined FTA rates for a swipe-based fingerprint sensor integrated in a commercially available laptop (Kukula & Elliott, 2006).

Finger	FTA Totals	Good Attempts	Total	Finger FTA %	Overall Contribution to FTA %
LI	30	88	118	25.42%	6%
LM	35	88	123	28.46%	7%
LR	45	88	133	33.83%	10%
LL	84	88	172	48.84%	18%
LT	17	88	105	16.19%	4%
RI	24	88	112	21.43%	5%
RM	42	88	130	32.31%	9%
RR	62	88	150	41.33%	13%
RL	102	88	190	53.68%	22%
RT	31	88	119	26.05%	7%
Overall	472		1352	34.91%	

2.7.4.3. NIST

To date, the NIST biometrics usability group has published three reports on the usability of biometric devices, one conference proceeding, and one document that outlines a taxonomy of usability and biometric definitions. In the subsequent sections, these five documents will be reviewed.

2.7.4.4. Portable biometrics workstation: session interface

The first biometric usability study released by NIST was performed by Young (2005). The purpose of the study was to assess how long data collection took for face, iris, and fingerprint recognition using a testing interface in order to maximize throughput and minimize stressors and unnecessary movements of the operator (J. Young, 2005). Contrary to most biometric testing evaluations, participants played the role of the operator, as the goal was to measure time to capture data using the interface. Data collection occurred in three scenarios: all three biometric modalities were in normal working condition, two devices were offline due to errors, and all devices appeared normal but there were three scanning errors. Results of the study showed that the average time to collect finger, face, and iris data was 208 seconds and 239 seconds in the first and last scenarios. It was also found that the participants committed few errors, with a majority being caused by incorrect prompting. Young (2005) also reports that the average time per scenario appeared to decrease as the scenarios progressed inferring that as the operator gets more experience, the time to collect the biometric data will decrease (p. 9). A survey was also provided to each participant after each scenario to capture data on the ease of use. Most participants felt the interface was easy to use and satisfaction generally increased with use (p. 11).

2.7.4.4.1. Strengths

Young (2005) outlined a number of procedures that are useful to measuring usability during a biometrics evaluation. This evaluation was also unique in that it examined techniques to streamline data collection. Also, this was the first reported document that classified the usability metrics in the realm of biometrics:

- Effectiveness – number of errors which were classified by (a) incorrectly or forgetting to prompt the assistant, (b) skipping a step that could be done, (c) accepting a corrupt image

- Efficiency – time to complete each session and task (finger, face, iris)
- Satisfaction – results of the questionnaire using a Likert scale on the ease and difficulty to collect data, remember tasks, time to perform the tasks, as well as using the interface (J. Young, 2005).

2.7.4.4.2. Weaknesses

While Young (2005) is useful for adapting usability to biometrics, the paper has limitations. First, the study only consisted of eight participants, which were very familiar with the interface, and specifically aided in the development of the interface. This fulfills one of the five design fallacies presented in Pheasant (2006) which is “if the design is satisfactory for me and will therefore be good for everyone else.” Thus, the participants used definitely threaten the conclusion validity of the report. Secondly, the report is difficult to follow and the testing protocol was vague, limiting the ability to replicate the study. Lastly, the report states that video was taken during of each test session and an observer took notes of the evaluation. However, none of this data was presented in the report. This data would have been interesting to examine for the biometrics community to evaluate for future research.

2.7.4.5. <u>Does habituation affect fingerprint image quality</u>

Theofanos, Micheals et al. (2006) reports a repeated measures experiment that sought to determine the effects of age, gender, and type of feedback, as well as habituation have on the image quality of fingerprints. The first two factors are well understood, but this study sought to understand the implications of different feedback: telling a user to start/stop a presentation, or indicate if the attempt was accepted, rejected, or was an acquisition failure. The experimental design occurred in two phases: no feedback and feedback. Both phases occurred over a three-week period, with participants interacting with the sensor before and after their lunch break. Right and left index fingers were used for approximately twenty images per participant. During phase one, participants were directed to place their finger on a sensor and received no feedback, in terms of quality or when the transaction was complete. The operator manually captured prints when the image stabilized on the computer display terminal. During phase two participants received feedback in real-time regarding image quality score and determined which fingerprint they wanted to save. In addition, participants were encouraged to continue interacting with the sensor until they received an NFIQ image quality score of three or better. Twenty-nine subjects participated in the phase one test that showed younger participants submitted higher quality prints than older subjects and the quality of the women's fingerprints were on average twenty percent worse than the males. There was also no presence of a habituation effect over the fourteen-day collection period. Phase two image quality scores mimicked those in phase one. In addition, feedback had no effect on the fingerprint quality of the young group, but improved with the older group over the course of the study, inferring older participants learned how to present better quality prints with more use of the sensor. Thus, it can be said people produced better quality fingerprints in fewer attempts when they received feedback. However, since participants were not given instructions on how to correct a “bad placement” in terms of position, pressure, et cetera, participants could not fully correct their interaction with the sensor.

2.7.4.5.1. Strengths

Theofanos, Micheals et al. (2006) evaluated the affect of feedback and habituation on the quality of fingerprint images and reveals a relationship between feedback and an improvement of quality / decrease in number of attempts, warranting more work in terms of habituation and type of feedback users need to receive to improve the human-biometric sensor interaction. Furthermore, the study confirms the conclusions made in Elliott, Kukula, and Sickler (2004), although with a smaller sample size and different image quality measurement.

2.7.4.5.2. Weaknesses

Theofanos, Micheals et al. (2006) cites Elliott, Kukula, and Sickler (2004) regarding the work on image quality and age. While the NIST study consisted of twenty nine and twenty eight subjects in the two respective phases, they claimed to have verified the claims made in the small scale study in Elliott, et al. (2004). It is interesting that the balanced block design with age as the factor had fifty-four subjects in each of the young and elderly groups for a total of one hundred eight subjects, where the combined NIST study was fifty-seven participants. Also, the paper offers no statistical analyses of the results, rather reports summary statistics and simple graphs.

2.7.4.6. A taxonomy of definitions for usability studies in biometrics

NISTIR 7378 (2006) is not a research report, rather it outlines a taxonomy to map terminology used in ISO/IEC JTC1/SC37 Standing Document 2 (SD2) – Harmonized Biometric Vocabulary (2007) to traditional terms used in usability studies. Moreover, the taxonomy presented attempts to use SD2 terminology, however the usability terms presented focus on user behavior as opposed to the traditional biometrics system-orientated viewpoint (International Organization for Standardization, 2007). To connect user behavior to the traditional biometrics terminology NISTIR 7378 (2006) presents the taxonomy by discussing presentations, attempts, and tasks to build a rubric that outlines the four results for a given biometric task. This is documented by four attempt classifications: acceptable conformant, unacceptable conformant, acceptable non-conformant, and unacceptable non-conformant, which the relationship is shown in Table 9, which has been adapted in this study. The parameters for this table are defined by acceptability, tasks, and conformance. Acceptability, or acceptable attempts fulfill the minimal capture requirements of a system and changes across the horizontal axis. Next, a task is a set of user behavior that defines an attempt. Lastly, conformance or a conformant attempt fulfills the requirements set out by a task and changes across the vertical axis (Micheals, Stanton, Theofanos, & Orandi, 2006).

Table 9 Taxonomy of types of user interactions (Micheals, Stanton, Theofanos, & Orandi, 2006)

	Acceptability	
Conformance	**Acceptable Conformant (A)** Right Index swipe that is presented and approved by the system	**Unacceptable Conformant (B)** Right Index swipe that is presented but rejected by the system
	Acceptable Non-Conformant (C) *Left* index that is presented and approved by the system	**Unacceptable Non-Conformant (D)** No presentation and system timeout

2.7.4.6.1. Strengths

NISTIR 7378 (2006) maps the different classes of definitions between two related fields. Moreover, the objective of NISTIR 7378 (2006) is to be a reference point for the biometrics community with the expectation that practitioners will further “refine the terminology to best fit their particular needs” (p. 1). This document served as starting point for the classification taxonomy created for the measurement of effectiveness / Failure to Acquire (FTA) used in this research.

2.7.4.6.2. Weaknesses

NISTIR 7378 (2006) falls short of discussing basic definitions for usability: effectiveness, efficiency, and satisfaction, and how they fit into the biometrics taxonomy. This is of importance as the biometrics community may choose to ignore this taxonomy since there is limited background for where this taxonomy derived from.

2.7.4.7. Effects of scanner height on fingerprint capture

NISTIR 7382 (2006) investigated if the height of a fingerprint sensor has an effect on fingerprint image quality for the Department of Homeland Security (DHS) in accordance with section 303 of the Border Security Act, codified as 8 U.S.C. 1732 and was briefly discussed in section 1.5.5.

NISTIR 7382 (2006) also used the usability metrics in ISO 9241-11 (1998) as the baseline for their measurements. Specifically, efficiency was measured, as the time required completing a task – the right slap, left slap, simultaneous thumbs, and single thumbs. Since the data did not follow a normal distribution, non-parametric tests were done. Friedman's two-way non-parametric tests, sign and signed rank tests, multiple range test were performed on the data. Results showed that the right slap was most efficient at the 30-six inch work surface height, although the only statistically significant value was found in the right slap task.

Effectiveness was measured in terms of NFIQ image quality across the four heights. To examine the data, the frequencies were computed for each finger across the table heights, which were analyzed with a chi-square test to investigate the significance of the differences among the distributions of quality scores (Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006). The results showed the differences among the observed/expected frequencies were reliable, except for the right index finger, suggesting the distribution of NFIQ image quality scores for the right index was the same across all four heights (Figure 44), but different for all other fingers. According to NISTIR 7382 (2006), this suggests the right index finger is not sensitive to height. Furthermore, the thumbs were found to be more sensitive to height than the slap-based fingerprints, as well as the left hand being more sensitive than the right slap.

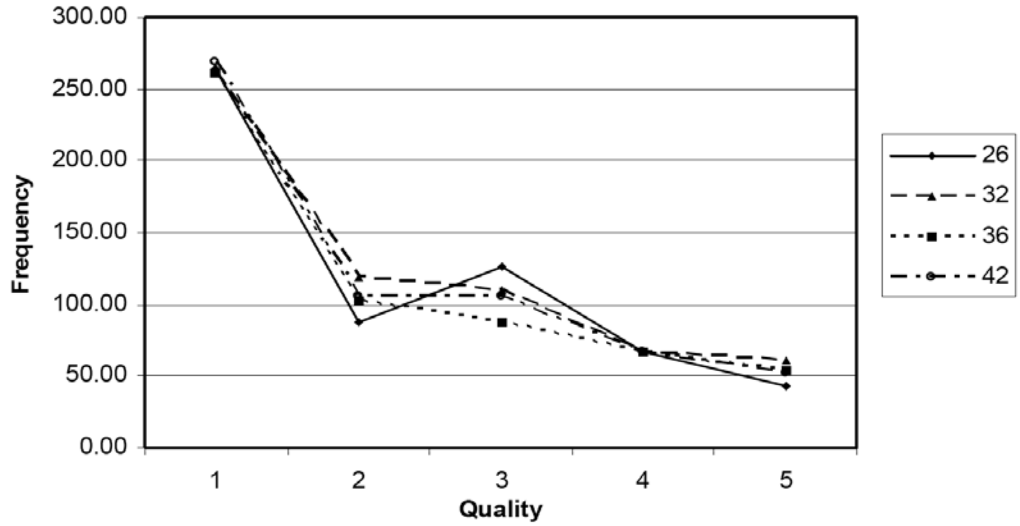


Figure 44 Right index finger quality distribution by height (Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006).

Lastly, user satisfaction was measured using a survey, which was distributed after completing the test. Results showed that participants found the 32 and 36 inch heights most comfortable and preferred the 32 inch height as shown in Figure 45.

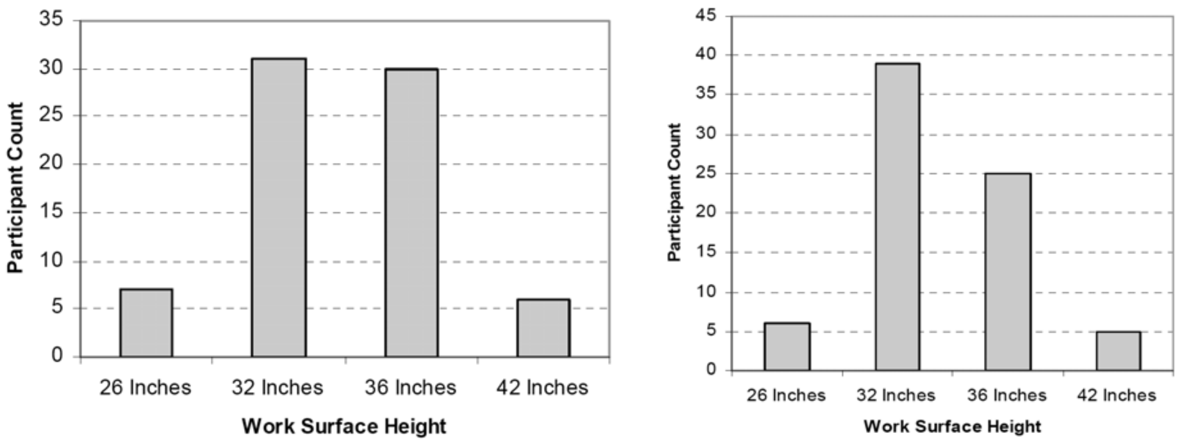


Figure 45 Participant response for comfort (left) and preference (right) (Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006).

2.7.4.7.1. Strengths

NISTIR 7382 (2006) was an evaluation for integrating usability research into biometrics. Furthermore it was similar to unpublished work by Kukula, Elliott, Tamer, and Senarith (2007) that investigated hand geometry match scores across four similar working heights. This document provides valuable information to base metrics and the testing protocol on for this dissertation.

2.7.4.7.2. Weaknesses

The main weakness of NISTIR 7382 (2006) is in the conclusion of the report, threatening the conclusion validity of the study. For example, the efficiency result is that the right slap required the least amount of time, thus is more efficient than the other tasks. However, in general, the work surface height was not a significant factor for time it took to complete a task. Additionally, the study only used NFIQ to assess image quality, rather than a continuous scale quality algorithm such as Aware WSQ.

2.7.4.8. Usability testing of 10-print fingerprint capture

The most recent work regarding usability or ergonomics outside of Purdue's Biometric Standards, Performance, and Assurance (BSPA) Laboratory has been conducted by the National Institute of Standards and Technology (NIST), which performed a usability test of 10-print fingerprint capture system (Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007). The purpose of this test was to evaluate the time required to collect a 10-print slap fingerprint image, as well as which method of instruction: poster, verbal, or a video was most effective. Specifically NISTIR 7403 (2007) had three research questions:

1. How long does it take to capture a 10-print image?
2. What is the impact of instructional mode on user performance?
3. What are the frequency and nature of the errors that occur in this process (p. 5)?

The study consisted of 300 participants that ranged in age from 18-65. 151 males and 149 females participated in the right and left slap, and simultaneous thumbs experiment. The instructional methods all portrayed similar information to complete the 10-print collection. The poster was a 76 cm by 115 cm, verbal consisted of instructions dictated by an operator, and the video was a soundless presentation of instructions approximately 50 seconds in length.

Results of the study showed that average time for 10-print capture without operator assistance was 48-64 seconds, with median range of 45-59 seconds and 50-54 seconds on average for operator assistance (median range of 45-46), suggesting that operators are critical to the acquisition process. In addition, 98% of the participants were able to complete the test with operator assistance. Regarding the instructional modes, participants using the poster had most difficulty with the fingerprint task as opposed to the other two methods. The average (median) times for the three methods were: 114.40 seconds (91.50 sec) for the poster, 86.40 seconds (65 sec) for the verbal, and 76.30 seconds (65 sec) for the video. Other times are shown in Table 10. Furthermore, only 17 participants trained with the poster completed the process error free, as opposed to 68 and 70 participants with the verbal and video modes. Forty four participants did not successfully complete the task with the poster, 5 with the verbal, and 13 with the video.

Table 10 NISTIR 7403 timings for the three instructional methods (Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007).

Method	Subjects	Instruction Time		Approach to sensor to end of capture		Software capture time		Total Time	
		μ	Median	μ	Median	μ	Median	μ	Median
Poster	52	31.27	29.6	114.4	91.5	64.13	58.5	145.67	126.85
Verbal	85	65.34	58.85	86.4	65	48.21	45	151.73	129.32
Video	85	86.93	81.15	76.3	65	50.87	46	163.22	152.18

2.7.4.8.1. Strengths

While NISTIR 7403 (2007) had severe limitations, the metrics outlined to measure effectiveness, efficiency, and satisfaction for biometrics were useful and transferable for this research.

2.7.4.8.2. Weaknesses

NISTIR 7403 (2007) evaluated the time to complete a 10-print capture and the effectiveness of three different methods of instruction, which were the variables of interest. However, during the presentation of the various instructional materials, different times were allotted for each of the methods. Specifically, a minimum of 45 seconds for audio, 50 seconds minimum for video, and the time for the poster was left to the participants' discretion (Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007). It is no wonder why the poster was significantly worse than the other two methods, as on average participants only spent about 31.27 seconds viewing the poster, whereas they spent 65.34 and 86.93 seconds for the verbal and video instruction methods, respectively. While it is interesting to know how long individuals would spend looking at a poster, when instructional method is the independent variable, this design is unacceptable as any conclusions made regarding the instruction are affected by not receiving the same amount of treatment.

In addition, there were data collection failures during the test, making about half the poster instruction method data unusable, resulting in an unbalanced design across the three methods: 52 subjects for the poster and 85 each for the verbal and video method.

2.7.4.9. UK Passport Trial

Maple and Norrington (2006) reported on the usability issues of United Kingdom's Passport Service (UKPS) Trial Program that utilized fingerprint, face, and iris recognition systems. The first problem found during the evaluation involved the working surface, which was positioned above the typical work height, forcing the user to sit with his or her feet not completely touching the floor (Maple & Norrington, 2006). Not only could prolonged exposure to a working environment such as this be harmful to individuals, but could ultimately affect the interaction and performance of the biometric system. Next, the face recognition system was evaluated. The physical setup was acceptable, as the camera was on an adjustable pole. However, the system orally instructed users to their remove glasses, and in some cases, the users had difficulty in seeing the equipment when their glasses were removed. The face system gave oral instructions to correct positioning, but the user could not judge how much to move based solely on these oral instructions. The iris system was investigated and the problem identified was again vision-related, as the ovals for alignment of the eye were almost indiscernible; users could not align using the oral instructions. Lastly, the fingerprint system was evaluated. The system was placed on a bench and required prints of all 10 digits. The author observed his fingers were wider than the surface area provided. Moreover, the two thumbs were collected at the same time, which was reported as awkward to reach by the user, who had to stand up to interact with the sensor.

Summarizing the findings reported by Maple and Norrington (2006), these observations on the practicality of the biometric systems could be made:

- Every user has his or her own unique set of personal physical and cognitive abilities,
- The physical environment of processes may impact results, and
- Delivery of instructions may affect successful user interaction with a system (p. 962).

2.8. Human-Biometric Sensor Interaction Conceptual Model

By combining the various methodologies discussed in the previous sections of this chapter, a new model outlining the characteristics of human-biometric sensor interaction can be developed. The HBSI applies components from biometrics, ergonomic principles, including anthropometry and biomechanics, as well as usability metrics shown together in Figure 46 to create a new conceptual model, which is shown in Figure 47.

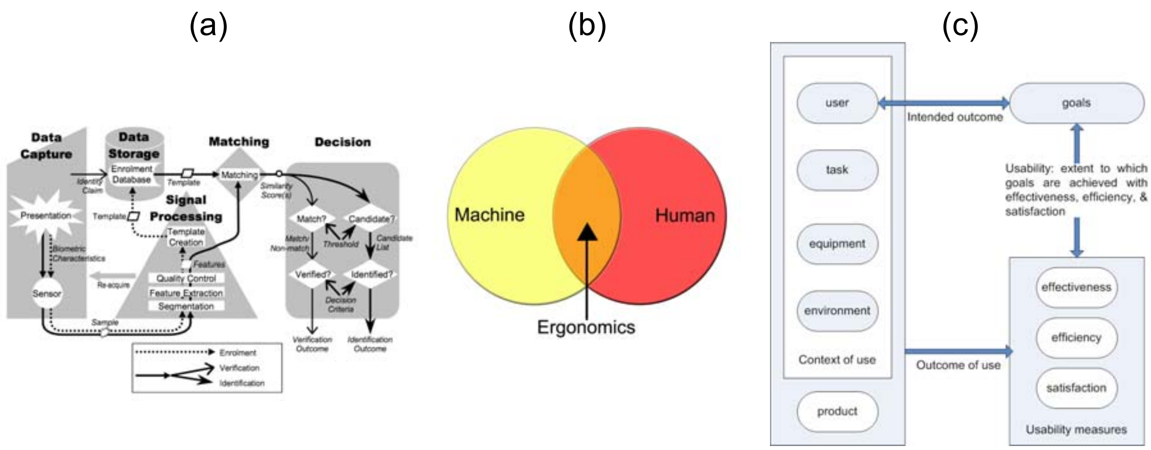


Figure 46 (a) General biometric model (International Standards Organization, 2006a); (b) general ergonomic model (Tayyari & Smith, 2003); and (c) general usability model (International Organization for Standardization, 1998).

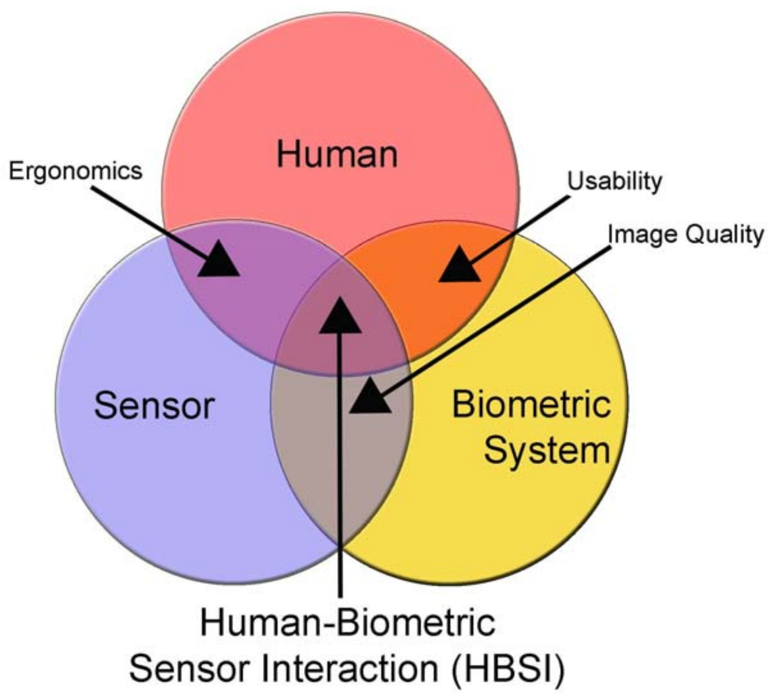


Figure 47 The Human-Biometric Sensor Interaction or HBSI conceptual model (Elliott, Kukula, & Modi, 2007; Kukula, 2007; Kukula, Elliott, & Duffy, 2007).

2.8.1. Human-Sensor

The human and sensor components of the HBSI model are similar to Tayyari & Smith's (2003) human-machine interaction model. Much like the traditional model, the human and biometric sensor components look to achieve the optimal relationship between humans and a biometric sensor in a particular environment. For the purposes of this research, this sensor is limited to physical interactive biometrics, meaning there is an actual "touching" of a sensor by a human. The overlap of these two sections is best summarized by ergonomics, which for the HBSI conceptual model means adapting the sensor so the *physical* interaction with a biometric sensor is more natural to the users.

2.8.2. Human-Biometric System

The human and biometric system components of the HBSI model are arranged in the model to accommodate the way biometric sensors, software, and implementations occur and are presented to users. A biometric sensor must not only be designed so a user can interact with it in a repeatable fashion, but the sensor(s), software, and the way the entire "system" is packaged must be usable. Usability according to ISO 9241-11 (1998) breaks down usability into three factors: effectiveness, efficiency, and satisfaction. Each of the three metrics is distinctively different and important to understand for products to strike a balance between the three. First, biometric systems must be effective, meaning users are able to complete the desired tasks without too much effort. Second, biometric systems must be efficient, meaning users must be able to accomplish the tasks easily and in a timely manner. Third, users must like, or be satisfied, with the biometric system, or will discontinue use and find alternative methods to accomplish the task.

2.8.3. Sensor-Biometric System

As mentioned in the previous two sections, users must be able to interact with a sensor in a consistent manner over time, while users must find the entire biometric system usable. To enable this to happen the third relationship of the HBSI conceptual model emerges, which is the sensor-biometric system, which measurable metric is image quality. Image quality is the important link between these two components because the image or sample acquired by the biometric sensor must contain the characteristics or features needed by the biometric system to enroll or match a user in the biometric system. So not only does the human-sensor relationship need to be functional and the human-biometric system need to be usable, the sensor-biometric system needs to be functional and this only occurs if the sensor captures and passes usable features onto the biometric system.

2.8.4. The Human-Biometric Sensor Interaction

In order to evaluate the model, the overlap of the Venn diagram has been expanded to reveal the proposed evaluation method for how each component that entails the HBSI can be measured, which is shown in Figure 48. Each component that is in the HBSI evaluation method has been shown to impact results in previous experiments from the respective field it was adapted from. Since the conceptual model is derived from different fields, each component usability, ergonomics, and biometrics produces a unique output. Thus, the final determination of the results is dependent upon the goals, objectives, and criteria the researcher, designer, or engineer is seeking, which is in-line with the ergonomics, usability, and design literature. Since work in this area is limited in biometrics, this study sought to find relationships within the HBSI evaluation method to report back to the biometrics community more insight when designing biometric devices. Moreover, the metrics used in this study may reveal a trade-off between performance versus usability, thus professional experience may be required to make the final determination of what aspects of a form factor design was most functional.

In prior iterations of the proposed HBSI evaluation method Fitts' Law was included as a dependent variable under the quantitative usability section. However, the data collected as the movement time in this study would have to include positioning computer mouse or other computer peripheral to start and stop a timer, thus the collected data would not be entirely of interest, and would likely bias the results. Therefore, in this evaluation Fitts' Law was not included. Like optimization, Fitts' Law may be included in future research, especially if task time is shown to be a significant factor in the evaluation method.

The following sections will describe each component of the proposed Human-Biometric Sensor Interaction evaluation method in terms of background literature, the components that were used in this study, and the type of analyses that were conducted.

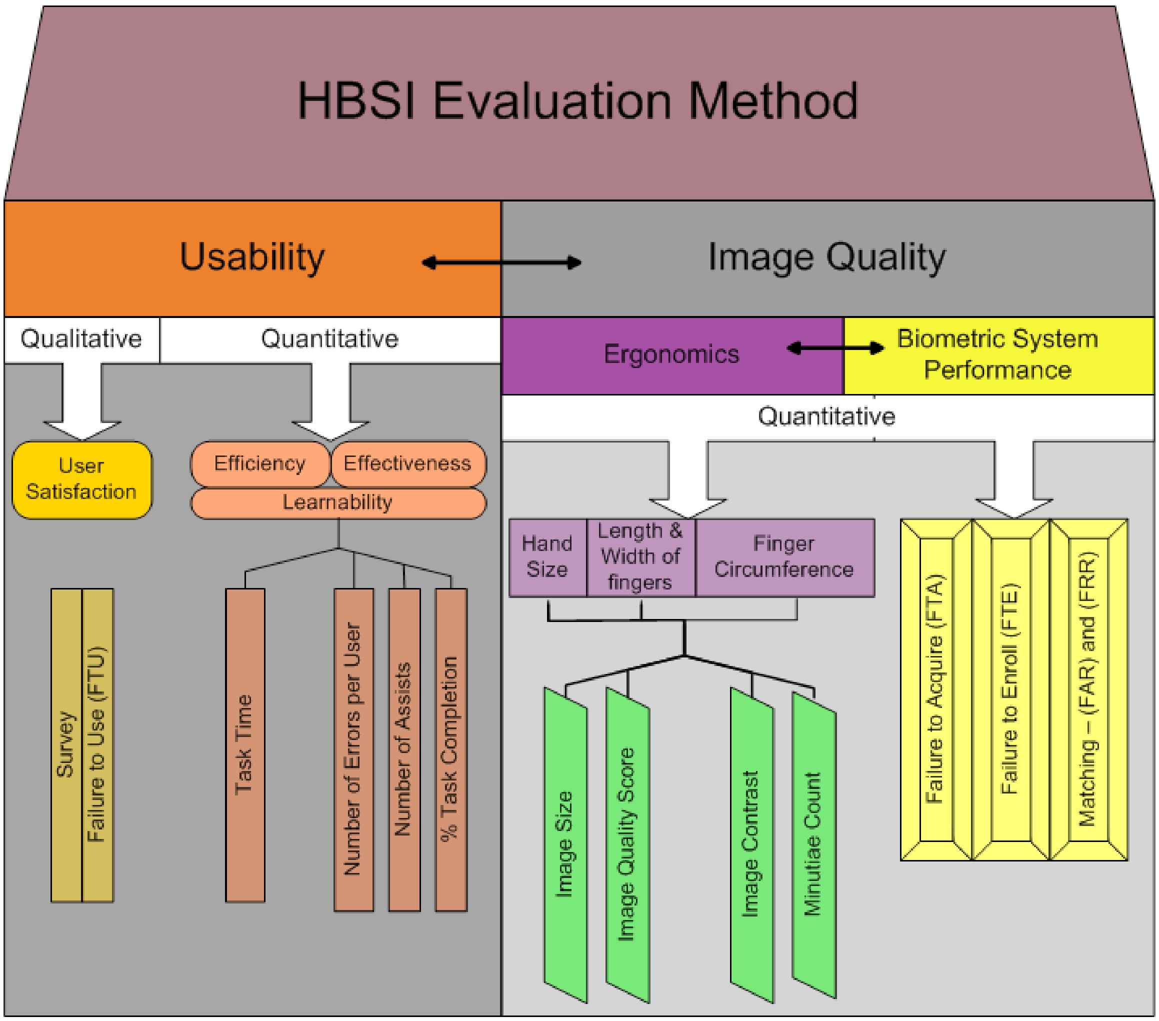


Figure 48 The HBSI evaluation method (Kukula, 2007; Kukula, Elliott, & Duffy, 2007).

2.8.4.1. Usability

As discussed in section 2.7.3 the usability metrics fall into two measurable categories: quantitative and qualitative, which will now be discussed.

2.8.4.1.1. Qualitative

2.8.4.1.1.1. Satisfaction

Multiple surveys and sources were considered to evaluate user satisfaction (International Standards Organization, 2006b; Kirakowski, 2007; Lewis, 1993; Rubin, 1994; Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006; Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007; J. Young, 2005). Two major factors in determining which survey to follow were reliability and number of questions. Since participants were tasked with returning for three visits to interact with four fingerprint sensors, asking them to complete a survey taking longer than five to 10 minutes seemed unreasonable.

From the surveys in the literature, Lewis's (1993) Post-Study System Usability Questionnaire (PSSUQ) and Kirakowski's (2007) Software Usability Measurement Inventory (SUMI). Both surveys provided previous results and validation, which were critical for use in this research; however SUMI contained fifty questions while the PSSUQ contained 19 questions. Thus, the PSSUQ was chosen and adapted for this study.

The PSSUQ consisted of nineteen 7-point Likert scale questions that was evaluated with 48 participants using a factor analysis (Lewis, 1993). Three factors emerged that accounted for 87% of the variability in the data, which were named: System Usefulness (SYSUSE), Information Quality (INFOQUAL), and Interface Quality (INTERQUAL) (Lewis, 1993). The survey was also measured in terms of reliability, validity, and sensitivity, which results appear in Table 11.

Table 11 Results of PSSUQ reliability, validity, and sensitivity analyses (Lewis, 1993).

Scale	Reliability *	Validity **	Sensitivity ***
		r(20) = .80, p = 0.0001	
Overall	0.97	r(29) = -0.40, p = 0.026	F(2,29) = 4.35, p = 0.02
SYSUSE	0.96	r(36) = -0.40, p = 0.006	F(2.36) = 6.9, p = 0.003
INFOQUAL	0.91	N/A	F(2,33) = 3.68, p = 0.04
INTERQUAL	0.91	r(35) = -0.29, p = 0.08	F(2,33) = 3.74, p = 0.03

* Coefficient alpha analyses
** Correlation analysis
*** Sensitivity ANOVA

For the purpose of this research, the 19 questions were adapted to evaluate user satisfaction for the three swipe-based fingerprint sensors that were used in the study. Note, the large area sensor was not evaluated for user satisfaction. Appendix A shows the original and adapted question sets, as well as the instructions that were given to the participants. The instrument was delivered online after completing the third visit. The data was analyzed using the appropriate analysis of variance test.

2.8.4.1.2. Quantitative

2.8.4.1.2.1. Effectiveness

Effectiveness was measured by number of errors in this study. User-interaction attempt errors are those that result in the user not performing the task as they were trained to do. This includes, but is not limited to: placing their finger in the wrong area, swiping the wrong segment/area of their finger, forgetting how to use the device, the system not returning an image when the subject interacted with the sensor, etc. To document these errors, an adapted form of the taxonomy from NISTIR 7378 (2006) was used in this research, which are documented by four attempt classifications: acceptable conformant, unacceptable conformant, acceptable non-conformant, and unacceptable non-conformant, which the relationship was presented earlier in Table 9. The parameters for this table are defined by acceptability, tasks, and conformance. Acceptability or acceptable attempts fulfill the minimal capture requirements of a system. Next, a task is a set of user behavior that defines an attempt. Lastly, conformance or a conformant attempt fulfills the requirements set out by a task (Micheals, Stanton, Theofanos, & Orandi, 2006).

The number of participants who were unable to complete a task (by sensor and finger) was also recorded. To further investigate the attempt level errors, the type of acquisition failure returned by the fingerprint system was also analyzed. Also, the number of errors that occurred by participants who successfully completed the task (by sensor and finger) was collected. The results of the taxonomy of attempts will be analyzed using chi-square tests, while the remaining data was presented in tables using frequencies.

2.8.4.1.2.2. Efficiency

Efficiency was measured by task time. Task time is the amount of time a participant needs to complete the training, enrollment, or matching mode for each sensor/finger combination. In order to maintain a consistent measure of task time each participant used a starting location marked in tape on the experimental setup area. Between each interaction the participant had to return their hand to this area. These metrics will then be analyzed across the three visits using the appropriate analysis of variance technique.

2.8.4.1.2.3. Learnability

Learnability was measured in terms of assisting users, completion percentage, and user effort. Assists are attempts, which the author provided an audio, visual, or physical cue to the participant.

Completeness was defined for this study as the sequence of events required to complete the overall task from for each finger/sensor/visit combination. Percent task completion was the percentage of the task that was successfully completed. This was computed for each sensor/visit combination.

Maximum user effort, or MUE, is a metric that compares the proportion of attempts needed to enroll/match on a particular sensor to the maximum number of interaction attempts allowed for that particular segment of the test. This was reported by sensor/visit/finger combination.

Appendix B outlines possible questions and actions that that were forecasted to occur and the author's anticipated response. The response was also marked as an assist and categorized appropriately. The general rule from NISTIR 7403 (2007) was adopted for this study, which states: "only prompt and make corrections during a session [interaction] if the participant communicates that a mistake was made" (p. 52). In addition to this rule, assistance was provided after four acquisition failures where the test administrator experienced the participant making an error.

2.8.4.2. Image Quality

As discussed in section 2.6.4.3, image quality is documented to impact the biometric matching algorithm (Jain, Chen, & Dass, 2005; Modi & Elliott, 2006b; Tabassi & Wilson, 2005; Yao, Pankanti, & Haas, 2004). As such, the image that results from the human-biometric sensor interaction may be influenced by the participant's anthropometry, attitude, ailment, etc, as well as the effectiveness of the biometric capture algorithm. However, limited work has focused on user anthropometry, attitude, and musculoskeletal disorders (MSDs). Studies have been conducted in the following areas and were discussed in the review of literature section: applied fingerprint pressure and image quality (Kukula, Elliott, Kim, & San Martin, 2007), FTA and FTE rates of swipe- and small- area fingerprint sensors (Kukula, Elliott, Wolleschensky, Parsons, & Whitaker, 2007), sensor height and performance of fingerprints (Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006) and hand geometry (Kukula, Elliott, Senarith, & San

Martin, 2006), swipe-based fingerprint FTA problems (Kukula & Elliott, 2006), user perspectives and performance of an implemented hand geometry device (Kukula & Elliott, 2005), and fingerprint performance by finger selection (Wayman, 2000; M. Young & Elliott, 2007). Since the biometric capture algorithm is outside the scope of this study, the focus is on the user. Thus, the image quality components of the HBSI evaluation method are based upon the resulting image from the human-sensor interaction.

2.8.4.2.1. Ergonomics

To account for human variability the following anthropometric measurements were collected to further understand the relationship of ergonomics and image quality: hand dimensions, finger dimensions, and finger circumference. In addition, the moisture level of the fingers was collected from the index finger of the dominant hand at the beginning of each visit. The specific anthropometric measurements are shown in Figure 49, with estimates shown in Table 12 are:

- Hand length (Middle finger to base of the hand) [1],
- Hand breadth (metacarpal) [12],
- Length of Index finger [4],
- Breadth of Index proximal interphalangeal joint (PIPJ) [10],
- Circumference of Index distal interphalangeal joint (DIPJ), and
- Skin Moisture, temperature, and elasticity.

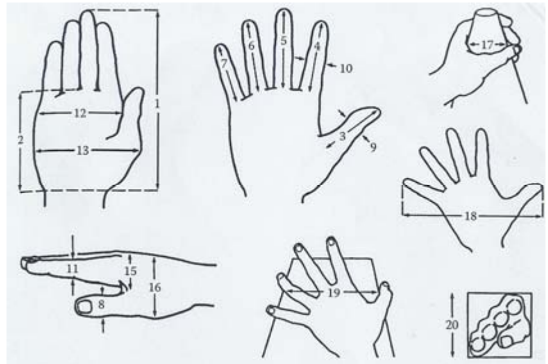


Figure 49 Anthropometry of the hand (Pheasant, 2006).

Table 12 Anthropometric estimates for the hand (in mm) (Pheasant, 2006).

	Men				Women			
Dimension	5^{th}	50^{th}	95^{th}	SD	5^{th}	50^{th}	95^{th}	SD
Hand Length (1)	173	189	205	10	159	174	189	9
Hand Breadth (12)	78	87	95	5	69	76	83	4
Index length (4)	64	72	79	5	60	67	74	4
Breadth of PIPJ (10)	19	21	23	1	16	18	20	1

2.8.4.2.1.1. Image Size

Image size was the first ergonomic variable of interest for the study. Image size was defined in this study as the maximum length of the fingerprint ridges in the image of interest and the maximum width of the fingerprint ridges. This variable was the first of multiple metrics that examine how well participants interacted with the swipe-based fingerprint sensor. Comparing the fingerprint images in Figure 32, one can see there is limited variability in the image size for those captured with the large area sensor. However, for the images captured with the swipe-based fingerprint sensor, there is variability both within subjects and across subjects, which can cause problems for the image quality and matching algorithms, and thus could impact the overall performance of a biometric system. This metric examined image size variability over time and across sensors and was analyzed using the appropriate analysis of variance technique.

2.8.4.2.1.2. Image Quality Score

The second measurement for ergonomics was the image quality score. Two measurements for image quality were used, one of which reported a continuous score and the other a nominal score. The two software packages were: Aware Wavelet Scalar Quantization (WSQ) VBQuality software v2.42E and the image quality algorithm in NIST Biometric Image Software (NBIS) package called NFIQ. The Aware WSQ software reported both image quality score and number of detected minutiae. The image quality score for Aware WSQ is a continuous variable with score values ranging from 0-99, with zero being a bad quality image score and 99 being the best quality score. The NIST NFIQ algorithm reported quality scores on a nominal scale from one to five, with one being best quality and five an image of lowest quality. The image quality score for Aware WSQ and the rank for NFIQ, as well as the number of detected minutiae were analyzed with the appropriate analysis of variance technique.

2.8.4.2.1.3. Image Contrast

The last measurement examined the variability in the fingerprint image attributes, or image contrast; specifically the gray levels that makeup the fingerprint image, to examine if a user could produce similar images repeatedly over time. This metric was one method of measuring it. If a device is easy to use, the user should have been able to swipe his or her finger with consistent speed, pressure, and direction across the sensor. Thus, this metric evaluated the gray levels of each fingerprint image and reported variations in the images as the standard deviation, and was analyzed with the appropriate analysis of variance technique.

2.8.4.2.2. Biometric System Performance

Technical performance testing has been used widely in the literature to measure the accuracy of biometric systems. Technical performance testing seeks to determine error and throughput rates, with the goal of understanding and predicting the real-world error and throughput performance of biometric systems (International Standards Organization, 2006a, p. vi). Throughout the literature, there are many metrics, protocols, and as can be expected with multiple protocols, contradictory results due to the variations. The following citations are only a small segment of testing protocols and evaluations that can be found in the biometrics literature, but reveal the need for a common standard set of metrics, definitions, and protocol outline (Barrett, 2000; Bone & Blackburn, 2002; Bouchier, Ahrens, & Wells, 1996; Fejfar & Myers, 1977; Holmes, Wright, & Maxwell, 1991; Maio, Maltoni, Cappelli, Wayman, & Jain, 2000; Mansfield, Kelly, Chandler, & Kane, 2001; Mansfield & Wayman, 2002; P. Phillips et al., 2003; P Phillips, Rauss, & Der, 1996; Zwiesele, Munde, Busch, & Daum, 2000). Likewise, Gray and Salzman (1998) discussed the importance of experimental design in their review of five of the more popular (in terms of citations) experiments that compared usability evaluation methods (UEMs) for practitioners in the field of Human-Computer Interaction (HCI). The authors discussed that small problems in design called into serious question the recommendations and advice given from the results of those experiments due to experimental design, statistical power, and other validity issues (Gray & Salzman, 1998). Thus, this research followed many of the definitions, criteria, and protocols contained in ISO/IEC 19795-1 (2006a) and 19795-2 (2007a) as they have been created from legacy reports, proceedings, and journal articles, as well as contributions from biometric experts from around the world.

The biometric system performance component of the HBSI model consisted of multiple metrics, which include FTA, FTE, FRR,FAR, and Detection Error Tradeoff (DET) curves, which will be discussed in the following sections.

2.8.4.2.2.1. Failure to Enroll (FTE) Rate

The FTE rate is defined as the proportion of the population that the biometric system fails to complete the enrollment process. This metric includes:

- Those unable to present the required biometric characteristic(s) or feature(s),
- Those unable to produce a sample of sufficient quality during enrollment,
- Those who cannot reliably produce a match decision with their newly created template during attempts to confirm the enrollment is usable (International Standards Organization, 2006a; Mansfield, Kelly, Chandler, & Kane, 2001).

FTE attempts were measured and reported for each sensor, finger, and visit combination. Each participant received one attempt to enroll on each fingerprint recognition system used in the evaluation. The enrollment attempt consisted of 30 presentations to produce 10 acceptable fingerprint images, which was defined as a successful enrollment.

The failure to enroll rate was an important metric for the HBSI evaluation method since if users cannot enroll on a swipe fingerprint device, there are likely issues with the device. However, there are no agreed upon standards for failure to enroll. Furthermore, enrollment algorithms vary from application to application and vendor-to-vendor, thus FTE analysis is dependent upon external factors besides the acquisition of an image or sample. Since all of the swipe-based fingerprint sensors are the same type of sensor and use the same acquisition algorithm, this rate can be compared to evaluate the performance of the different form factors. However, FTA is considered a more robust measure for this study and will be discussed in the next section.

Data analysis for the FTE rate included a comparison of the rate, as well as the number of attempts and transactions across the four evaluated sensors and for the right and left index fingers.

2.8.4.2.2.2. Failure to Acquire (FTA)

Similar to the FTE rate is the FTA rate. The FTA rate is defined as the proportion of verification or identification attempts for which the system fails to capture or locate an image or signal of sufficient quality; which may include attempts where extracted features are substandard. The acquisition or quality control threshold will be documented as (ϕ) in this study. This metric includes:

- Attempts where the biometric characteristic cannot be presented,
- Attempts for which the segmentation or feature extraction fail,
- Attempts in which the extracted features do not meet the quality control thresholds (International Standards Organization, 2006a).

The metric for FTA was separated into two levels in this evaluation: presentation and transaction. Both were measured and reported for each sensor, finger, and visit combination. Each participant received one transaction, which they had to provide 10 acceptable fingerprint images on each of the four sensors. Each participant was allowed 30 presentations to produce the 10 images. Therefore, the transaction level FTA rate was the proportion of transactions that failed to produce any of the required 10 images. The presentation level FTA rate was the proportion of presentations that failed to produce an image.

The FTA rate was also an important metric for the HBSI evaluation method since if users cannot produce fingerprint images over time on a swipe fingerprint device, there are likely issues with the device. Since all swipe-based fingerprint sensors were the same type of sensor, this rate was compared to evaluate the performance of the different form factors. The FTA was reported by number of FTA attempts, as well as a rate by sensor, finger, and visit.

Moreover, unlike the FTE rate, the FTA rate was a more appropriate measure for this study because even though samples are acquired during an enrollment sequence, the enrollment may fail due to extraneous constraints the enrollment procedure must satisfy. Furthermore, this study examined the usability of fingerprint recognition devices, and a sensor that provides the most repeatable images, thus the binary result of a sensor acquiring an image or failing to acquire is of much more importance. In addition, the fingerprint technology that is used changes the parameters of an FTA. For example, optical fingerprint sensors function much like a digital camera, thus maybe able to capture fingerprints from a wider range of the population with varying properties, whereas capacitance sensors may not be able to acquire images from individuals with dry fingerprints, for example. Furthermore, large area fingerprint sensors require users to place and hold their finger pad on a fairly large area for the sensor to acquire an image, whereas with swipe-based fingerprint technologies users have to align their finger with the width of the sensor *and* swipe the appropriate part of the finger along the sensor to acquire an image. Thus, the acquisition process for swipe-based sensors is much more complex than for large-area sensors and the resulting FTA rates may be higher.

2.8.4.2.2.3. Receiver Operator Characteristic (ROC) Curves

Computer vision, machine intelligence, and image analysis originates from Artificial Intelligence (AI) in the 1950s and early 1960s which can be defined into three generations: mathematics, algorithms, and testing (Clark & Clark, 2005). First generation techniques were based on mathematics that examined pixel values in surrounding areas of images. Processing was done in batch jobs line by line. As the area developed so did the complexity of the programs. Thus second-generation techniques utilized algorithms to do comparisons, which significantly reduced processing time. According to Clark & Clark (2005) the field is currently in the early years of the third generation that is concerned with issues relating to testing and comparing algorithms. This research extends the comparison to evaluate differences in sensors and fingers, like previous research conducted by Wayman (2000) and Young and Elliott (2007). One of the main tools developed to evaluate images is with receiver operating characteristic (ROC) curves. ROC curves were developed during World War II to assess performance of radar operators and distinguish between friends and enemies (Clark & Clark, 2005). Since WWII, ROC curves have been adapted by the medical field to separate sensitivity and specificity and more recently in the biometrics community to determine correct and incorrect trials or matches.

A receiver operating characteristic (ROC) curve is a plot of false acceptance rate against the true match rate, as a parameter, the decision threshold (τ) in biometrics, is varied, which can be seen in Figure 50. The plot “highlights the trade-off between the true positive rate and the false positive rate" (Clark & Clark, 2005, p. 7).

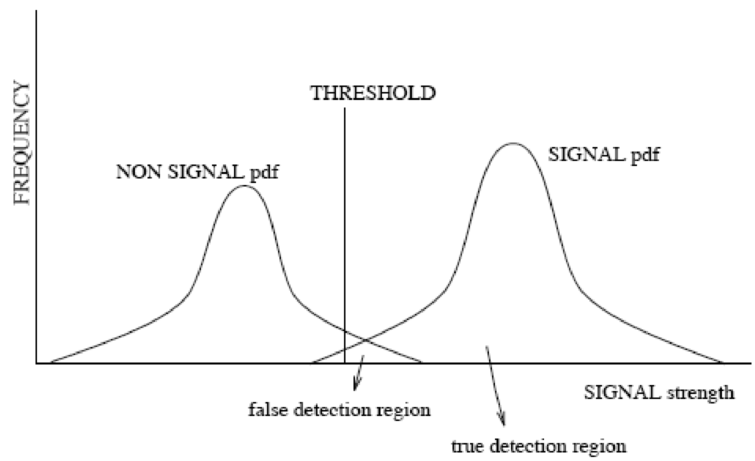


Figure 50 Example signal and non-signal probability density functions (PDF) (Courtney & Thacker, 2001).

Specifically, the plot places the false positives on the x-axis against the corresponding rate of true positives, or 1-FNMR, on the y-axis plotted parametrically as a function of the decision threshold (International Standards Organization, 2006a; Mansfield & Wayman, 2002). A general equation is shown in (2) and example ROC curves are shown in Figure 51.

$$ROC(\tau) = [FMR(\tau), TAR(\tau)]; \text{ where } \tau \text{ is the system threshold} \qquad (2)$$

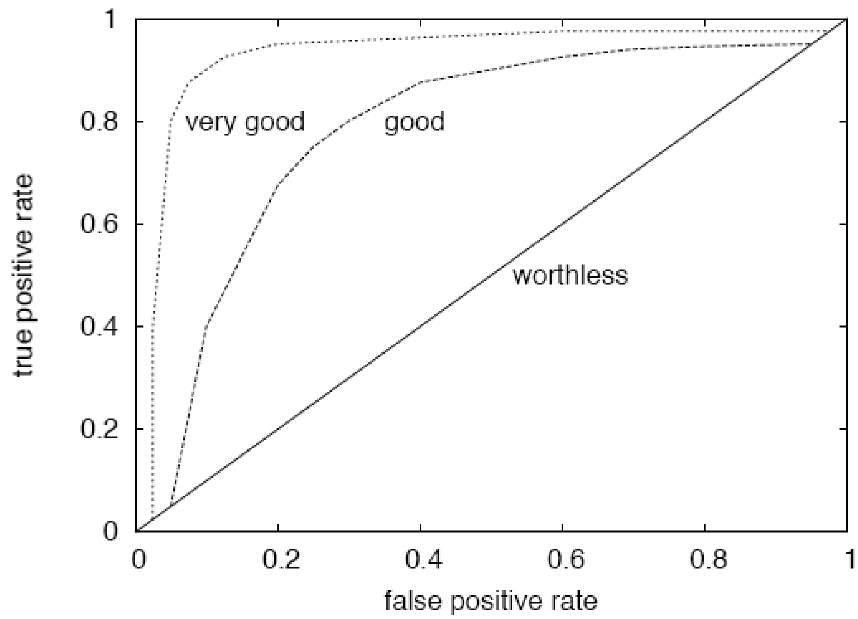


Figure 51 Example ROC curves (Clark & Clark, 2005).

Confidence limits can also be added to the plot as error bars or error ellipses around the points of interest to provide a more accurate depiction of the trial. An ROC curve is assessed in the following way. The closer the curve approaches the top-left corner of the plot, the more accurate the test, while the closer the curve is to a forty-five degree diagonal, the worse the test. In addition, the area under the curve is an accuracy measure of the test (Clark & Clark, 2005). There is no convention for orientating the ROC curve, however the two most common use raw data and log-log.

The ROC curve assesses performance by running an algorithm with data where the truth is known and counting correct and incorrect trials. Each test can produce four results:

1. True positive, also known as true acceptance or true match, yields a correct match.
2. True negative, also known as true rejection or true non-match, yields a correct non-match.
3. False negative, also known as false rejection or a false non-match, or Type I error, as it yields a non-match when it should have matched.
4. False positive, also known as false acceptance, false match, false alarm, or Type II error, as it yields a correct match when it should have produced a non-match (Clark & Clark, 2005).

An alternative method for graphically comparing the performance of biometric systems is called a Detection Error Trade-off (DET) curve, which is a modified ROC curve (Doddington, Kamm, Martin, Ordowski, & Przybocki, 1997). A DET curve is a plot of the false acceptance rate versus the false rejection rate, giving "equal emphasis to both types of error", as shown in Figure 52 (Clark & Clark, 2005).

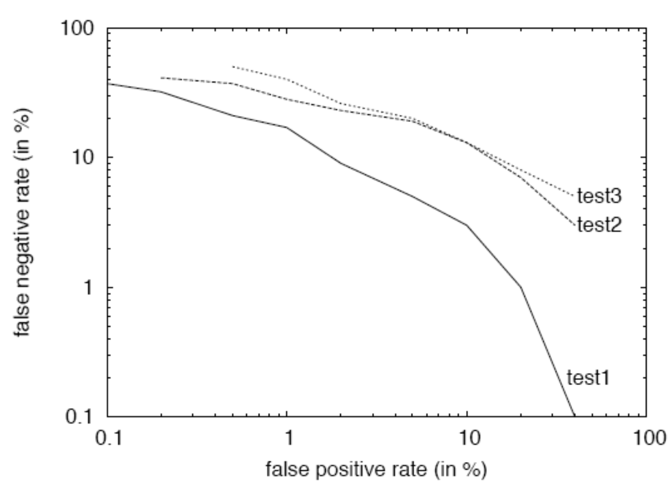


Figure 52 Example DET curves (Clark & Clark, 2005).

A DET curve typically places the False Accept Rate (FAR) or False Match Rate (FMR) on the x-axis and False Reject Rate (FRR) or False Non-Match Rate (FNMR) on the y-axis as function of decision threshold (International Standards Organization, 2006a). A general DET equation is shown in(3).

$$DET(\tau) = [FMR(\tau), FNMR(\tau)]; \text{ where } \tau \text{ is the system threshold} \tag{3}$$

According to Clark & Clark (2005), “DET curves usually utilize logarithmic scales on both axes”, which “tend to be more spread out than ROC curves, making it easier to distinguish individual algorithm’s results” (p. 8). DET curves that appear as a straight line show that the distributions are likely normal; meaning if the log-log scale were not used the curve would be bell shaped (Clark & Clark, 2005). Another method of analysis of the plot is the equal error rate (EER), which is the point where FAR and FRR intersect, where the smaller the EER the better.

The analysis for this study was performed offline, once all the data was collected. DET curves were generated, one for each finger/system/visit combination. If data analysis provided insight to a particular component that was interesting to investigate, post hoc analyses were developed. This is of interest to the HBSI evaluation method as the same participants using the index finger of both hands interacted with three swipe fingerprint sensors that are exactly alike, using the same extraction and matching algorithm, with the only difference being the form factor. Furthermore, it was interesting to compare the performance of the large area capacitance sensor of the same vendor with their swipe-based sensors with both commercial and developed form factors.

2.8.4.2.2.4. True Positive

True positives are defined as transactions made by users who are enrolled in the system and the user's correct identifier is the one returned indicating a correct match. The true positive rate is also known as true acceptance or true match rate.

This metric was originally to be measured in terms of verification, or a one-to-one matching scenario and performed by the matching algorithm online, which recorded the result of each match attempt and store the time-stamped result in a log file. The verification rates were also to be reported as a percentage. Due to modifications that will be discussed later in the methodology, this rate is no longer included in the analysis.

2.8.4.2.2.5. True Negative

True negatives are defined as transactions made by users who are either not enrolled in the system or claim a different identity and the claimed user's identifier is not returned indicating a correct non-match. The true negative rate is also known as true rejection or true non-match rate.

This metric was not measured in this study, as it was outside the scope of the performance criteria established in the HBSI evaluation method.

2.8.4.2.2.6. False Negative

False negatives are defined as transactions made by users who are enrolled in the system but the user’s correct identifier is not returned indicating a non-match when it should have matched. This metric is also known as the FRR, FNMR, or Type I error (Clark & Clark, 2005). The biometrics community has categorized false negatives into two common metrics: false rejections and false non-matches. Both metrics are inter-related as the FNMR is part of the FRR.

FNMR is defined as the proportion of genuine attempt samples falsely declared not to match the template of the same characteristic from the same user supplying the sample (International Standards Organization, 2006a). The false declaration was caused by a genuine attempt that was passed to the matching subsystem or algorithm and the resulting similarity score produced was below the decision threshold.

Similarly, the FRR is defined as the proportion of verification transactions with truthful claims of identity that are incorrectly denied (International Standards Organization, 2006a). Moreover, the FRR includes transactions denied from both matching errors and those due to FTA presentations, which is shown in (4).

$$FRR(\tau) = FTA(\phi) + FNMR(\tau) * [1 - FTA(\phi)] \tag{4}$$

where τ is the decision threshold and ϕ is the quality control or acquisition threshold

This was measured offline once data collection was complete, in order to correctly fulfill the components of the equation. This was an important component of the HBSI evaluation method as it examines not only the matching performance but also combines the individuals who had issues interacting with the sensor and produced acquisition failures. FRR were computed for each sensor/finger combination, as well as by visit and reported on the y-axis of the DET curves.

2.8.4.2.2.7. False Positive

The last performance classification is false positives. False positives are defined as transactions made by users who may or may not be enrolled in the system and produce a correct match to a user's identifier that is not their own and should have produced a non-match. This metric is also known as the False Acceptance or Alarm Rate (FAR), False Match Rate (FMR), or a Type II error (Clark & Clark, 2005). The biometrics community has categorized false positives into two common metrics: false accepts and false matches. Both metrics are inter-related as the FMR is part of the FAR.

FMR is defined as the proportion of zero-effort impostor attempt samples, meaning the individual submits their own biometric characteristics as if they were attempting to match themselves, but are falsely declared to match the compared non-self template (International Standards Organization, 2006a). Moreover, false matches are caused by genuine or zero-effort impostor attempt that are passed to the matching subsystem or algorithm that results in a similarity score that is above the decision threshold.

Similarly, the false acceptance rate (FAR) is the proportion of verification transactions with wrongful claims of identity that are incorrectly confirmed

(International Standards Organization, 2006a). Moreover, the FAR requires that samples submitted for comparison are not rejected by the quality control or acquisition threshold (ϕ), which is shown in (5).

$$FAR(\tau) = FMR(\tau) * [1 - FTA(\phi)] \text{, where } \tau \text{ is the decision threshold and } \phi \text{ is the quality control or acquisition threshold} \quad (5)$$

Like the FRR, the FAR was measured offline once data collection was complete, in order to correctly fulfill the components of the equation. This was included in the HBSI evaluation method but is not as central as the FRR calculation. FAR were computed for each sensor/finger combination, as well as by visit and reported on the x-axis of the DET curves.

2.8.5. Hypotheses

Hypothesis testing is used in research experiments to test a pair of competing assertions made by researchers involving two or more variables. The competing hypotheses are known as the null and the alternate. The null hypothesis is typically created such that it is the inverse of what the researcher expects to happen to the dependent variable, allowing the data to contradict it. Conversely, the alternate hypothesis is designed so the independent variable(s) will have an effect on the dependent variable. The proposed evaluation model enables one to evaluate each component: usability – both qualitatively and quantitatively, as well as the image quality, which is the overarching measure for both ergonomics and typical biometric performance metrics.

In this study, the independent variable was the form factor design, which contains four levels:

1. Commercial swipe-based sensor (UPEK)
2. Ergonomic form factor design 1 (PUSH)
3. Ergonomic form factor design 2 (PULL).
4. Commercial large-area sensor (LA)

There were many dependent and controlled variables in this study, some of which have been discussed in previous sections, while the controlled variables will be discussed in the methodology section. All hypotheses were evaluated against an alpha level (α) of 0.05.

2.8.5.1. Efficiency, Effectiveness, Learnability, and User Satisfaction

There is much literature that discusses efficiency, effectiveness, learnability, and user satisfaction and possible metrics that are used to evaluate them (Bailey, 1982; Booth, 1989; Chignell & Hancock, 1992; Gould & Lewis, 1985; Grandjean, 1988; International Organization for Standardization, 1998; Mayhew, 1999; Micheals, Stanton, Theofanos, & Orandi, 2006; NIOSH, 1997; Rubin, 1994; Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006; Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007; Woodson, 1982). Metrics that were used in this evaluation included: number of errors per participant, number of assists the administrator provided to participants, and the percent of task completion. The hypotheses that evaluated the quantitative usability metrics were:

1. The new form factor(s) will be significantly different in terms of the number of errors a user produces during interaction with a swipe based fingerprint sensor than the commercially available form factor.
2. The new form factor(s) will be significantly different in terms of the number of assists a user requires during interaction with a swipe based fingerprint sensor than the commercially available form factor.
3. The new form factor(s) will be significantly different in terms of the task completion rate with a swipe based fingerprint sensor than the commercially available form factor.
4. The new form factor will be significantly different in terms of the maximum user effort (MUE) required with a swipe based fingerprint sensor than the commercial available form factor.
5. The new form factor(s) will be significantly different in terms of the user satisfaction score with a swipe based fingerprint sensor than the commercially available form factor.
6. The new form factor(s) will be significantly different in terms of the amount of time a user requires to complete the task with a swipe based fingerprint sensor than the commercially available form factor.

2.8.5.2. <u>Ergonomics: Biomechanics & Anthropometry</u>

The measures for ergonomics investigated the anthropometric measurements and biomechanics of the hand and wrist through the measurements in the vertical green bars of Figure 48: fingerprint image size, the image quality score, the contrast of the image, and the minutiae count. The ergonomics literature discusses larger hands being more productive (Salvendy, 1971), whereas the biometric literature states that larger fingers are better performing in terms of matching (Wayman, 2000; M. Young & Elliott, 2007). Thus, the hypotheses are as follows:

7. The new form factor(s) will be significantly different in terms of the reported gray level (image contrast) within a swipe-based fingerprint image for all hand and finger sizes compared to the commercially available sensor.
8. The new form factor(s) will be significantly different in terms of the image quality score of a swipe-based fingerprint image for all hand and finger sizes compared to the commercially available sensor.
9. The new form factor(s) will be significantly different in terms of the fingerprint image size of a swipe-based fingerprint image for all hand and finger sizes compared to the commercially available sensor.
10. The new form factor(s) will be significantly different in terms of the number of minutiae detected in a swipe-based fingerprint image for all hand and finger sizes compared to the commercially available sensor.

2.8.5.3. Biometric Performance

It is well documented in the biometrics literature that image quality affects biometric system performance. In addition, interaction errors also contribute to acquisition and enrollment errors as discussed earlier in this chapter. Thus the hypotheses that will evaluate biometric performance are:

11. There is a significant difference in the Failure to Acquire (FTA) rate of the new form factor(s) and the commercially available form factor.
12. There is a significant difference in the Failure to Enroll (FTE) rate of the new form factor(s) and the commercially available form factor.
13. There is a significant difference in the match rate of the new form factor(s) and the commercially available form factor.

2.8.6. Statistical Analysis

In addition to reporting the results in tables, as ratios, and in the form of ROC or DET curves as discussed in section 2.8.4.2.2.3, the data was further investigated using statistical analyses, which will be discussed in this section. As this study attempted to validate the HBSI evaluation model, numerous variables from three areas: usability, ergonomics, and biometric performance were collected and analyzed. The following statistical analyses were planned, however further post hoc tests may be formulated if the data warranted further investigation.

The rationale for conducting the statistical analyses was to provide further understanding of the collected data to validate the proposed HBSI evaluation method for swipe-based fingerprint recognition devices. While ratios and rates are fundamental to understanding performance, conclusions and recommendations based entirely upon them would be a severe threat to the conclusion validity of the study. Therefore, statistical analyses helped to understand if there are relationships in the data and the significance of it. Thus to investigate if relationships are indeed in the data, the following statistical methods were used if appropriate: diagnostics, correlation matrices, chi-square, t-tests, analysis of variance, and regression. The following sections will be dedicated to each of the following methods and how the statistics will be applied. Once all the different statistical models are discussed, tables will be presented as to which methods will be used to analyze the factors of interest.

2.8.6.1. Diagnostics

Before beginning the statistical analyses, the data were examined for violations of normality, independence, and homogeneity of variance, as well as multicollinearity for regression. Each statistical model used has certain assumptions that must be met in order for the result to be valid. Each of the diagnostic measures will now be discussed.

2.8.6.1.1. Normality

The first step is to check the normality of the data, because underlying most statistical tests is the assumption of multivariate normality, which is the assumption that each variable and all linear combinations of the variables are normally distributed (Tabachnick & Fidell, 1996). Therefore, the data was analyzed for normality by creating normal probability plots (qq plots) for each examined variable, residual plots such as predicted versus residuals and sequence versus residuals. The latter is crucial to this study as it involves repeated measures – multiple attempts per sensor and multiple visits. If the data violates this assumption, the appropriate remedial measure, such as transformation were sought to correct it, if possible. If the violation cannot be mitigated, non-parametric tests were conducted. Furthermore, statistical analyses performed with percentages will likely cover a broad range, the arcsine transformation will likely be used as Neher (2003) states it is appropriate when the percentages range is greater than forty percent.

2.8.6.1.2. Independence

The next step examined the data for relationships between the collected variables. In order to check the strength and direction of existing linear relationships between the data, Pearson correlation matrices were performed on the data and reported in the results section if needed. If there are relations amongst the variables, it will pose problems for regression, particularly the model selection, which is known as multicollinearity.

2.8.6.1.3. Homogeneity of Variance

Another diagnostic measure before proceeding with analysis of variance statistical tests is to satisfy the assumption of homogeneity of variance, which is the assumption that the variance amongst the groups is equal. If they are not equal, the data is referred to as heteroscedastic. To test for homogeneity of variance, Levene or Bartlett’s test was performed on the data.

2.8.6.2. Chi-square test for independence

According to Tabachnick and Fidell (1996), chi-square test of independence examines relationships between two discrete variables, which is also known as contingency analysis. In this study, it analyzed the classification type of attempts: acceptable conformant (A), unacceptable conformant (B), Acceptable non-conformant (C), and Unacceptable non-conformant (D) versus the form factor type: ergonomic 1 (PUSH), ergonomic 2 (PULL), commercial (UPEK), and large area (LA). Chi-square tests are defined by the hypothesis: H_o: the attempt type is independent of the form factor and H_a: the attempt type is not independent of the form factor, with the test statistic shown in (6).

$$\chi^2 = \sum_{i=1}^{k} (O_i + E_i)^2 / E_i \, , \qquad (6)$$

where O_i is the observed frequency for bin *i* and E_i is the expected frequency for bin *i*. The expected frequency is calculated by $E_i = N[F(Y_u) - F(Y_l)]$, where *F* is the cumulative distribution function for the distribution being tested, Y_u is the upper limit for class *i*, Y_l is the lower limit for class *i*, and *N* is the sample size (NIST/SEMATECH, 2006).

Furthermore, if χ^2 small, meaning the observed frequencies are similar to the expected value, the null hypothesis is retained, and the conclusion that the two variables are independent (Tabachnick & Fidell, 1996). However if χ^2 is large, the two variables are said to be related and the null hypothesis is rejected. This study explored the data to see if a tested form factor is related to a particular attempt classification.

In order to compare proportions for a particular factor and determine if statistically significant differences exist in all possible pairs of proportions, the Marascuillo procedure for multiple proportions was used (NIST/SEMATECH, 2006). The procedure, which is outlined in NIST's *e-Handbook of Statistical Methods* (2006), consists of three steps. First, it assumes samples of size n_i (*I* = 1, 2, …, *k)* from *k* populations and computes the differences ($p_i - p_j$, where $i \neq j$) among all $k(k-1)/2$ pairs of proportions. The absolute values of the computed differences are the test-statistics. The second step uses the χ^2 table to find the table value based on the number of factors and significance value to compare to the computed critical values computed from (7). Lastly, compare each all *k*(*k*-1)/2 test statistics against the corresponding critical r_{ij} value against the defined significance value (NIST/SEMATECH, 2006).

$$r_{ij} = \sqrt{\chi^2_{(\alpha,k-1)}}\sqrt{\frac{p_i(1-p_i)}{n_i} + \frac{p_j(1-p_j)}{n_j}} \qquad (7)$$

2.8.6.3. Two-Sample t-Test for Equal Means

One method to determine if the new form factor designs improve the human-biometric sensor interaction is to compare results from each of the new form factor designs (i) to each other, then (ii) to the commercially available form factor. In addition, the post-study satisfaction survey was evaluated using t-tests. This test will seek to answer if the form factors are equivalent or if one is better than the others or if a change in satisfaction occurred with one form factor over another. (8) reveals the two-sample *t*-test equation, with hypothesis H_o: $\mu_1 = \mu_2$ and H_a $\mu_1 \neq \mu_2$.

$$T = (\overline{Y}_1 - \overline{Y}_2) \Big/ \sqrt{\left(s_1^2 / N_1 \right) + \left(s_2^2 / N_2 \right)} \qquad (8)$$

, where N is the sample size, Y is the sample means, and s are the sample variances.

2.8.6.4. Analysis of Variance

The selected method for analysis of variance will depend entirely upon the diagnostic results. There are two basic types: parametric and non-parametric. Parametric testing is the preferred method of analysis, however will be dependent upon meeting model assumptions.

2.8.6.4.1. Parametric

The parametric method is known as Analysis of Variance, or ANOVA. ANOVA tests are an instrument to compare the effect of multiple levels of one or more factor(s) on a response variable, which is also a generalization of the two-sample *t*-test. Parametric tests involve hypothesis testing and require a stringent set of assumptions that must be met (NIST/SEMATECH, 2006). The ANOVA is partitioned into two segments: the variation that is explained by the model (9) and the variation not explained, or error (10), which are both used to calculate the *F*-statistic (11) testing the hypotheses H_o: $\mu_1 = \mu_2 = \ldots = \mu_I$ and H_a: not all μ's are the same. In practice, *p* values are used, but the $F_{observed}$ test statistic can also be compared to the *F* distribution table as shown in (12). Typically, when the H_o is rejected the variation of the model (SSM) tends to be larger than the error (SSE), which corresponds to a larger *F* value.

$$SSM = \sum \left(\hat{Y}_i - \overline{Y}\right)^2, dfM = 1, MSM = SSM/dfM \quad (9)$$

$$SSE = \sum \left(Y_i - \hat{Y}_i\right)^2, dfE = n - 2, MSE = SSE/dfE \quad (10)$$

$$F = MSM/MSE \sim F(dfM, dfE) \quad (11)$$

$$F \geq F(1-\alpha, dfM, dfE) \quad (12)$$

2.8.6.4.2. Non-parametric

According to Montgomery (1997), in situations where normality assumptions fail to be met, alternative statistical methods to the *F* test analysis of variance can be used. Non-parametric methods are those that are distribution free and are typically used in the following situations:

- Measurements are categorical,
- Parametric model assumptions cannot be met, or
- Analysis requires investigation into features such as: randomness, independence, symmetry, or goodness of fit, rather than testing hypotheses about values of population parameters (NIST/SEMATECH, 2006).

One of the more common non-parametric methods was developed by Kruskal and Wallis (1952; , 1953). The Kruskal-Wallis test examines the equality of medians for two or more populations and examines the hypotheses H_o: the population medians are all equal and H_a: the medians are not all the same, with the assumptions that samples from the different populations are independent random samples from continuous distributions with similar shapes (Minitab, 2000). The Kruskal-Wallis test computes the *H* statistic, which is shown in (13).

$$H = \left[\frac{12}{N(N+1)}\right]\sum_{i=1}^{a}\frac{R_{i\cdot}^{2}}{n_i} - 3(N+1), \qquad (13)$$

where *a* equals the number of samples (groups), n_i is the number of observations for the i^{th} sample, *N* is the total number of observations, and R_i is the sum of ranks for group *i* (NIST/SEMATECH, 2006).

2.8.6.5. Regression

In addition to the analyses that examined the relationship between the four form factor types (independent variable) and the multiple dependent and controlled variables, regression was used to examine if relationships existed between the continuous variables, such as the image quality scores, gray level variance, or image area and the controlled variables (anthropometric data or collected meta-data) in order to predict a result of one variable from one or more variables (Tabachnick & Fidell, 1996). A general equation with *k* predictors for multiple regression is shown in (14).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + E, \qquad (14)$$

where *Y* is the response variable, β's are the regression coefficients, X's are the independent variables, *E* is the error component reflecting the difference between an individual's observed response *Y* and the true average response (Tabachnick & Fidell, 1996).

Since the purpose of multiple regression analysis is to "describe the extent, direction, and strength of the relationship between several independent variables and [one or more] continuous dependent variable[s]", specifying the maximum model and selecting a viable model was of utmost importance in this exploratory study of the human-biometric sensor interaction (Tabachnick & Fidell, 1996, p. 12). Once the maximum model was specified, model selection was performed in SAS using the following criteria: R^2, adjusted R^2, Mallow's C_p, AIC, and SBC. After a viable model was chosen, the assumptions were checked to ensure the model is reasonable.

2.8.6.6. Repeated Measures

The various statistical methodologies that were planned in this study were outlined. However, in those discussions, one crucial component was missing; the fact that multiple measures were taken over multiple attempts and visits. This is known as repeated measures. According to Montgomery (1997) much experimental work uses people, thus the measured unit differs in experience, training, and background therefore the responses of each individual to the same treatment may be vary substantially and must be controlled. One control for this is the amount of demographic, user experience, and explanatory variables that were collected during the study, which are outlined in the Methodology section. Furthermore, a balanced design is sought to include equal groups of experienced versus inexperienced users, young versus old, gender types, and anthropometric data to form the randomized blocks according to Kleinbaum, Kupper, Muller, and

Nizam (1998). Also, recall that a correlation matrix was computed for all collected variables to account for human variation across the tested population.

Similarly, this study consists of three visits where participants interact with four fingerprint sensors. Thus, the ordering of the sensors will be pseudo-random using an program developed in the Biometric Standards, Performance, and Assurance Laboratory to reduce the possibility of systematic error due to expected improvement on the last device compared to the first (habituation), which may threaten the validity of the study (Zevecic, Miller, & Harburn, 2000). Each sensor and finger combination was randomly ordered.

2.8.6.7. Outline of Statistical Methods

In the previous sections, overviews of various statistical methods were presented. To assist in choosing which statistical tests were appropriate Tabachnick and Fidell (1996) and Hartman (2000) were referenced.

Table 13 reveals which statistical methods were used, except for regression, which is outlined in Table 14.

Table 13 Outline of statistical methods used with listed variables.

HBSI component	Statistical Method	Dependent Variable	DV Type	IV	Control Variable
Effectiveness	chi-square	Total number (and classification type) of attempts	Cat	Form Factor	See bottom of table
Usability	ANOVA	Survey scales	Con	Form Factor	
Efficiency	ANOVA	Training Task Time	Con	Form Factor	
	ANOVA	Enrollment Task Time	Con	Form Factor	
	ANOVA	Matching Task Time (v1,2,3)	Con	Form Factor	
Learnability	ANOVA	Number of Assists	Cat	Form Factor	
	ANOVA	Task Completion			
	ANOVA	Maximum User Effort (MUE)			
Ergonomics	ANOVA	Image Size (area)	Con	Form Factor	
	ANOVA	Image Quality	Con	Form Factor	
	ANOVA	Number of Minutiae	Con	Form Factor	
	ANOVA	Gray Level variation	Con	Form Factor	
Biometric Performance	ANOVA	FTA attempts (see Effectiveness)	Con	Form Factor	
	ANOVA	FTE transactions	Con	Form Factor	
Controlled Variables: age, experience with biometrics, MSDs, Anthropometric measurements, hand, finger, Ethnic origin					
KEY: Cat = categorical, Con = continuous, Pro = proportion, (x) = number of levels					

Table 14 Outline of regression models to be examined.

HBSI Component	Dependent Variable	Independent Variables
Effectiveness	Number of Attempts	All possible combinations of variables will be considered. Model selection will examine if any of the collected variables can predict the response/dependent variable.
Efficiency	Training Task Time	
	Enrollment Task Time	
	Verification Task Time	
Learnability	Number of Assists	
Ergonomics	Image Size (area)	
	Image Quality	
	Variance in gray levels / Image Contrast	
	Minutiae Count	

CHAPTER 3. METHODOLOGY

This study had four objectives: (a) analyze the literature to determine what influences the interaction of humans and biometric devices, (b) develop a conceptual model based on previous research, (c) design two alternative swipe fingerprint sensors, and (d) to compare how people interact with the commercial and designed swipe fingerprint sensors, to examine if changing the form factor improves the usability of the device in terms of the proposed HBSI evaluation method.

This research consists of three studies or phases. The first phase was the qualitative component, which consisted of single visit interviews of fingerprint users, ergonomic experts, and non-users to gather feedback on their use of a commercial swipe-based fingerprint sensor to aid in the design of the two alternative swipe-based fingerprint sensors based on the results of the interviews. The second phase was design and fabrication of the two form factor devices. Alongside the results of the qualitative study, principles in the usability, ergonomic, and biometric literature were also used to create the swipe-based fingerprint form factors. The third phase of this research evaluated the two designed swipe-fingerprint sensors to a commercial swipe fingerprint sensor using the HBSI evaluation method. This chapter is presented by phase and consists of three parts: 1) Qualitative data collection, 2) Design and fabrication of the swipe sensors, and 3) Quantitative data collection. The research timeline for the three parts is shown in Table 15.

Table 15 HBSI research timeline.

Time	Action
8/2004 - 7/2007	Literature review and development of the HBSI conceptual model
8/2005 - 12/2007	Preliminary experiments involving human interaction
11/2006	HBSI evaluation method established and revised through 7/2007
9/2007 - 11/ 2007	Formulation of qualitative study materials.
11/2007 - 12/2007	Phase 1: Qualitative data collection
12/2007 - 1/2008	Phase 1: Qualitative data analysis
1/2008 - 2/2008	Phase 2: Form factor prototype design and fabrication
2/2008 - 4/2008	Phase 3: Quantitative data collection
4/2008 - 5/2008	Phase 3: Quantitative data analysis
5/2008 - 6/2008	Final documentation preparation

3.1. Phase 1: Qualitative Data Collection

The purpose of the qualitative phase was to obtain feedback from individuals to design a more usable swipe-based form factor. The population sample was drawn from individuals ranging from biometric novices, ergonomic experts, and non-users.

Qualitative research typically presents findings that stem from three different types of data collection efforts: 1) in-depth, open-ended interviews; 2) direct observation; and 3) written documents (Patton, 2002). Interviews were chosen as the method of interest as they yield “direct quotations from people about their experiences, opinions, feelings, and knowledge” (Patton, 2002, p. 4).

These methods are data rich and are better equipped to inform researchers about participant experiences, as opposed to surveys and questionnaires that quantify experiences as a simple statistic. Prior quantitative investigations in the area of swipe-based fingerprint recognition revealed problematic areas with the human-sensor interaction, thus qualitative data was needed to give substance to why users were having issues with the swipe sensors, and furthermore if they liked using them. Thus, the purpose in using qualitative methods was to more fully understand biometric users, non-users, and ergonomic experts experience with biometrics, specifically swipe-based fingerprint recognition devices, their thoughts and feelings regarding commercial devices, as well as components that they like, dislike, or feel that are missing in current swipe-based fingerprint devices in order to design a device that was intended to be more usable.

3.1.1. Theoretical Framework for Phase 1

The theoretical framework for the qualitative study was based upon two qualitative research and evaluation methods: phenomenology and systems theory. According to Patton (2002) phenomenology derives from research in philosophy and aims to find the "meaning, structure, and essence of the lived experience of this phenomenon for this person or a group of people" (p. 104). Systems theory answers the foundational question of how and why a system as a whole function as it does (Patton, 2002). In this study, systems theory is the relationship and interaction between the human and fingerprint devices, with the guiding question for the qualitative inquiry being based on the interaction between the human and the device. In addition, phenomenology was used to learn more about participants lived experiences; either with ergonomics, biometrics, or by choosing not to use biometrics. The purpose of including such data underlies the goal of usability; separating what works in theory and what is effective and allows the user to be more efficient in an everyday environment that individuals also find satisfying. The central question the interviews attempted to answer was: what criteria do users, non-users, and ergonomic experts believe should be included in the form factor of a swipe-based fingerprint sensor to make it more usable, comfortable, and efficient for users?

3.1.2. Research Design for Phase 1

The design of the qualitative study consisted of three data sources to strategically triangulate the results and allow for a comprehensive analysis. The three sources of data were: audio recordings, video recordings of the interaction between the interviewee and fingerprint sensors, and notes made by the author. The three methods ensured information rich details would not be lost. Including the different methods allowed the author to listen *and* watch what the participant was doing. In addition, the notes the author took during the interview sessions allowed for improved recall if a statement or action of interest occurred. The interview instrument developed for this study was based upon the four interview variations discussed in Patton (2002), which are shown in Table 16.

Table 16 The different variations in developing interview instrumentation (Patton, 2002, p. 349).

Type of Interview	Characteristics
Informal conversational interview	Questions emerge from the immediate context and are asked in the natural course of things; there is no predetermination of questions topics or wording.
Interview guide approach	Topics and issues to be covered are specified in advance, in outline form; interviewer decides sequence and wording of questions in the course of the interview.
Standardized open-ended interview	The exact wording and sequence of questions are determined in advance. All interviewees are asked the same basic questions in the same order. Questions are worded in a completely open-ended format.
Closed, fixed-response interview	Questions and response categories are determined in advance. Responses are fixed; respondent chooses from among these fixed responses.

The interview instrument used combined three methods: the informal conversational interview, the interview guide approach, and the standardized open-ended interview, as the topics and issues were specified in advance. The questions were worded the same for each participant, but question sequencing was dependent upon the course of the interview. If a participant response was interesting, additional probing questions were asked for improved comprehension of the participant's response. The probing questions were not scripted, but were based upon simple inquiry questioning strategies, such as:

- You stated _______ , could you further explain what you mean?
- Why?
- To make sure I understand what you are explaining, could you please show me with the sensors in front of you?

The author was extremely careful to not state questions that led a participant to respond in a particular way, but to elicit responses based upon the experience of the participants. Combining the three strategies assisted in overcoming some of the weaknesses discussed in Patton (2002) for each interview type. First, the list of questions provided for comparable data across all participants as each responded to each question, yet provided more flexibility than a traditional standardized open-ended interview as the questioning strategy was dependent upon the course of the interview and the flow of participant responses. Secondly, the use of the standard set of questions overcomes the weakness of a traditional guide approach that results in questions that are worded differently, which can cause variations in results. Lastly, the informal conversational interview components that were used in this study helped to increase the relevance of the results by building on previous responses and observations to more fully understand a participants’ response, interaction issue, or design issue.

3.1.3. Volunteer Crew for Phase 1

This sampling strategy for the qualitative component was criterion sampling, which investigates individuals that meet some criteria (Patton, 2002). For this investigation, participation was open to everyone, but specific groups were targeted during recruitment, especially ergonomic experts from Purdue University, individuals who have used swipe-based fingerprint recognition and other biometric devices prior to this research, and individuals who have not used biometrics, or who oppose the use of biometrics. These three groups were chosen to reduce the bias towards the technology and ergonomics perspective.

3.1.4. Recruitment of Subjects for Phase 1

Participants were informed of the study through one of the following channels: announcements before and after classes, email distribution to past biometric testing participants, and email and discussions with ergonomic and usability colleagues. Those who agreed to participate in the interview made an appointment. Upon arrival on the day of the interview, participants were instructed to read, understand, and sign a consent form (Appendix C). After the consent form was signed, the author explained the type of questions and the format of the interview to the participant to inform them about the purpose and procedures of the study and to inform what information was being collected from them. Personal demographic information was collected, including gender, occupation, ethnicity, age, handedness, questions about familiarity with biometrics, and if the participant suffered from musculoskeletal ailments.

3.1.5. Confidentiality in Phase 1

To participate in the study, each participant provided consent to the collection of his or her personal demographic information, the audio recording of their voice, and the video recording of their interaction with the fingerprint sensors. Each participant was given a unique identification number that was associated with the audio and video data stored on the storage media along with the demographic information. Names were not associated with the data collected. Video recordings only included the participants' hands interacting with the sensors, which recorded area is shown in Figure 53.

Figure 53 Area that was video recorded during the qualitative interviews.

3.1.6. Testing Procedure for Phase 1

Upon completion of the consent form paperwork and introduction to the study, the author started the audio and video recording. The video recording device was setup such that the participant's face was not in the field of view of the camera (Figure 53). The audio recording device recorded both the author and the participant's voice so that the data could be transcribed and analyzed offline. The experimental setup area that the participant interacted with is shown in Figure 54.

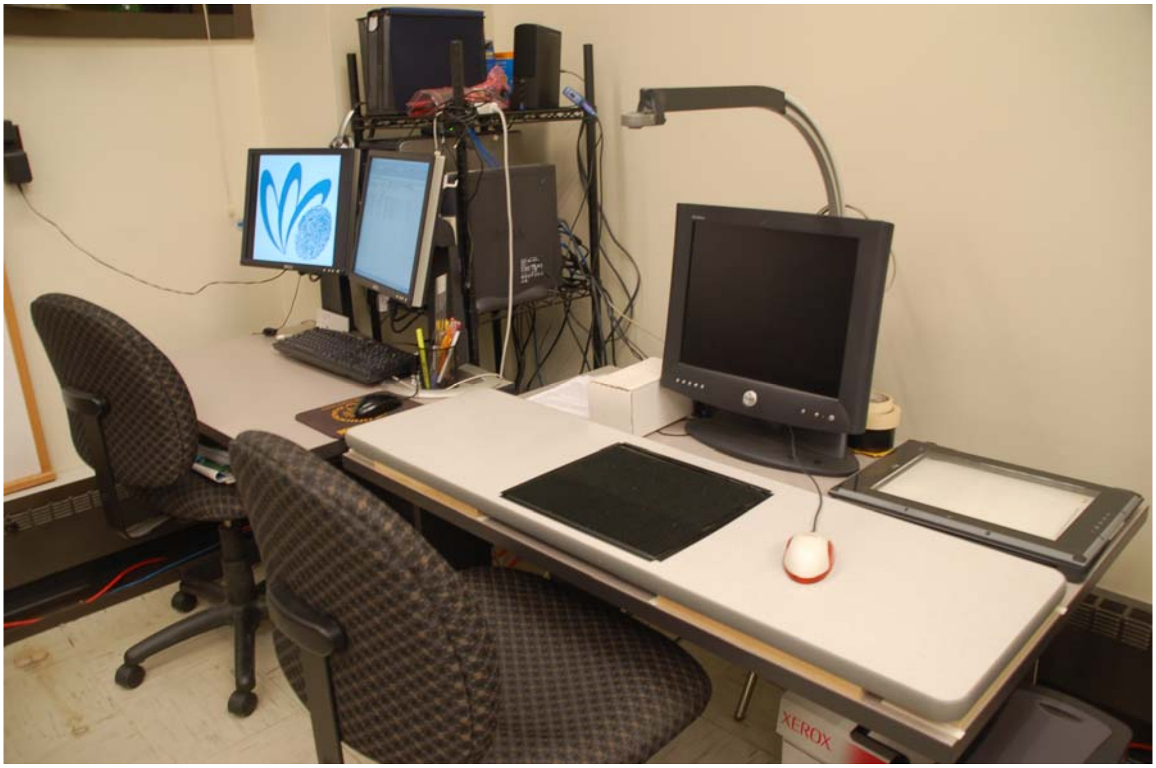


Figure 54 Experimental setup for the qualitative data interview.

3.1.6.1. <u>Interview Questionnaires for Phase 1</u>

Two interview guides were developed, one for biometric users, and one for biometric non-users, and ergonomic experts. The different questionnaire guides were developed to collect similar data across the three groups, however questions had to be worded differently due to each participant's experience with biometrics or knowledge of ergonomics and usability. Thus, one interview guide was used for the biometric users, whereas a second guide was developed for the ergonomic experts and biometric non-users. Both questionnaire guides included questions regarding usefulness, effectiveness, efficiency, satisfaction, and designing an alternative device. The questionnaire for biometric users can be found in Appendix D, while Appendix E contains the questionnaire for non-users and ergonomic experts. As mentioned earlier, the interview questions were open ended and the participant had the opportunity to illustrate with the sensors what they were attempting to communicate to the author. During the entire interview, the commercially available UPEK sensor was positioned in the black square area (Figure 53), as this was the sensor the fingerprint recognition users had previously used. During the questions regarding alternative designs, two additional commercial swipe-based fingerprint sensors were introduced along with the UPEK sensor (Figure 55) to allow participants to illustrate what they were attempting to communicate to the author.

Figure 55 Swipe fingerprint sensors used as visual aides during the qualitative interviews. Sensors were labeled long silver [UPEK] (left), round (middle), and square (right).

All interviews were audio and video taped. Observation logs were also kept for each participant so the author could make notes that would aid transcription of the interviews. An example interview/observation guide for one fingerprint user, ergonomic expert, and fingerprint non-user can be found in Appendix F. Transcription of the data occurred as soon as practically possible after the interview to ensure as much information from the interview session could be recalled. All interviews were moderated and transcribed by the author, reducing the threats to internal validity due to multiple interviewers collecting or individuals transcribing the data.

3.1.7. Equipment in Phase 1

A Dell Optiplex GX620 Pentium 4 3.4Ghz computer was used throughout the qualitative data collection and analysis portion of this study. Audacity 1.2.6 was used to record and encode the audio of the interviews, while Microsoft Windows Movie Maker 5.1 was used to record the interaction of the participant with the fingerprint sensors during the interviews. NCH Swift Sound’s Express Scribe v4.16 was used for transcribing the interviews. Weft QDA v1.0.1 was used to perform a textual analysis on the transcripts and create the initial coding scheme based on the three interview groups. Once this was complete, the information was exported to Microsoft Excel 2007 for further manipulation and data analysis.

3.2. Phase 2: Design and Fabrication of the Swipe-Based Fingerprint Form Factors

The qualitative analysis (Phase 1) results were analyzed with principles of ergonomic design to create the two designed form factors for this study. This comparison was done to assure that the results of phase 1 were inline with the literature. Solid Works 2007 SP3.1 software was used to create solid models of the two form factors. Once the solid models were complete, CAM Works 2007 SP4.0, a Computer-Aided Manufacturing (CAM) software solution created the automated tool paths in the form of Computer Numerical Control (CNC) code. Once the simulations were successful, the parts were milled in the College of Technology's Machine Tool Laboratory located in MGL 1208. The Hurco VM1 vertical machine center (Figure 56) was used to mill the form factors using the tools listed in Table 17. As the author was not trained to operate the Hurco machine center, a systems technologist from the Department of Manufacturing Engineering Technology operated the mill. However, the author created the models and CNC code.

Figure 56 Hurco VM1 vertical machine center used to fabricate the swipe-based form factor devices.

Table 17 Machine tools used in the Hurco VM1.

Tool	Description
3	¼ inch End Mill
8	¼ inch Ball Nose
10	1/8 inch End Mill
12	Center Drill
13	1/16 inch End Mill
21	¼ - 20 Tap (7)

3.3. Phase 3: Quantitative Data Collection

Once the fabrication and assembly of the two designed form factors was complete the experimental setup area was finalized, pilot tested, and process mapped. Upon completion of the tasks mentioned above, the quantitative data collection on three swipe sensors and one large area sensor began. The quantitative data collection was described as a scenario-based test, which is classified in Table 18.

Table 18 Evaluation Classification (Mansfield & Wayman, 2002).

Experimental Application Types	Classification for this research
Application Classification	Scenario
Co-operative or Non Co-operative	Co-operative Users
Overt versus Covert	Overt
Habituated versus Non-Habituated	Both
Attended versus Non-Attended	Attended
Standard Environment	Yes
Public versus Private	N/A
Open versus Closed System	Closed

3.3.1. Volunteer Crew for Phase 3

The methodology for the quantitative data collection was based upon the cross-sectional framework that consisted of participants from a population of students, faculty, university employees, and individuals from the Greater Lafayette community that were over the age of 18. The data collection effort consisted of three visits. Criterion and chain sampling were utilized to attempt to collect data from a broad spectrum of participants so a block design could be developed and subsequently used for data analysis. Approximately one hundred appointment slots were made available for this study. Data collection occurred between 8:00 A.M. and 9:00 P.M. for the duration of the study. The final sample size, completing all three visits, was 85. The volunteer crew was examined by the following demographic information:

- Age: Less than 30, 30 – 50, and over 50
- Gender: Female and Male

- Ethnic origin
    - American Indian / Alaska Native
    - Asian
    - Black
    - Hispanic
    - White
- Handedness: Right, Left, and Ambidextrous
- Experience with biometrics: self-report fingerprint sensor types
- Musculoskeletal Disorders of hands and fingers: Self-reported
- Anthropometric measurements, which were ranked according to the volunteer crew as small (0-33rd percentile), medium (34-66th percentile), and large (67-100th percentile) for:
    - Hand size: Length and breadth
    - Index finger length
    - Breadth of the index proximal interphalangeal joint
    - Breadth of the index distal interphalangeal joint
    - Circumference of the index distal interphalangeal joint of the dominant hand.

3.3.2. Recruitment of Subjects in Phase 3

Participants were informed of the study through announcements made at the end of class, through posters displayed around campus, and emails that were sent out to various groups, list serves, and to prior participants through the appointment management website. Those wishing to participate in the study made an appointment online. When an individual arrived for their first visit, they were instructed to read, ask questions, and sign the quantitative study consent form (Appendix F) if they decided to participate in the study. After signing the consent form, participants were instructed to watch an audio and video based MS PowerPoint presentation (Appendix H), outlining the procedures that were to be completed during the study, as well as what information was to be collected. Since participation in this study was entirely voluntary, participants were allowed to withdrawal from the study at any time. Only two participants, who completed visit one, did not complete the study. These two individuals did not indicate that they wished to withdraw from participation; rather, they did not show up to the subsequent appointments they made during visit one. The dropout rate of the final volunteer crew was 2.29%, whereas the recruitment effort resulted in 103 total visit 1 appointments, which 18 did not show and failed to reschedule, producing a failure to participate rate of 17.48%.

3.3.3. Confidentiality in Phase 3

A unique identification number was assigned to each participant, which was located on the front of the consent form in both plain text and in the form of a matrix bar code. These unique identification numbers were the only association with the individual’s collected personal characteristics and fingerprint images collected. All fingerprint images stored on the computer are only identifiable by the unique identification number only. Personal characteristics and background information were collected through a survey instrument using the participant's assigned unique identification number and stored on a computer hard drive protected by password. Fingerprint Images collected were also stored on a computer hard drive that was protected by password. All fingerprint images were analyzed offline once data collection was completed.

3.3.4. Potential Risks to Subjects in Phase 3

This study had minimal risk on the participants, which was no more than one would encounter in everyday life. The study consisted of three visits that required participants to swipe or place their right and left index fingers on a fingerprint sensor over repeated attempts. Each participant was given as much rest as needed between attempts to maintain an acceptable level of comfort during the study. As these sensors are available in the marketplace in multiple forms, such as: personal data assistants (PDAs), USB flash drives, cellular telephones, and commercial laptops, participants were subjected to no additional risk than they would encounter in everyday life. Furthermore, participation was voluntary and participants could have chosen to withdraw from the study at any time.

3.3.5. Record Keeping in Phase 3

All fingerprint image data collected as part of this research was stored, organized, and followed a naming convention that is shown below. This promotes repeatability of research, as well as an understanding of the data for future experiments involving the data.

In addition, any manipulation of the original data set, such as format changes of a face image, are saved as separate files which are traceable to the original image, maintaining a continuous progression of the experiments and analysis process. For example, all original images were collected as .PGM files, but were converted to both .BMP and .WSQ for data analysis. The data exists in all three forms, which is shown in Table 19. The two fingers used were the right and left index fingers and were abbreviated as RI and LI, respectively. There were 3 data collection components (DCC): training (T), enrollment (E), and matching (V); and three visits: visit 1 (V1), visit 2 (V2), and visit 3 (V3). The sensors were UPEK (1), PUSH (2), PULL (3), and the large area (4).

Table 19 Fingerprint image naming convention for the three formats used.

SUBJECT	FINGER	DCC	SAMPLE	VISIT	SENSOR	EXTENSION
001	RI	E	01	V1	1	.pgm
001	RI	E	01	V1	1	.bmp
001	RI	E	01	V1	1	.wsq

3.3.6. Room Specifications

The evaluation took place in Knoy Hall of Technology in the Biometrics Standards, Performance, and Assurance Laboratory in room 378. Figure 57 shows the author and participant data collection areas that were used.

Figure 57 Full view of experimental testing area. The computer on the left is the researcher station. The computer on the right is the data collection computer where participants interacted with the fingerprint sensors.

3.3.7. Equipment Used in Phase 3

This section discusses the equipment used for the quantitative data collection study. Each section below discusses the computer equipment, biometric devices, and other measurement and recording devices used in detail. Appendix N contains a listing of all equipment used in the study.

3.3.7.1. Biometric Devices

The biometric hardware devices that were used in this evaluation were donated by UPEK, Inc. Three commercially available fingerprint swipe-based sensors and one large area fingerprint sensor were donated for the purpose of this study. The commercial swipe sensors are the UPEK Eikon 3C/42 USB fingerprint reader. The commercial large area sensor is the UPEK TCRU1C TouchChip USB fingerprint reader. The four fingerprint sensor form factors can be seen in Figure 58. All four sensors remained in the author’s possession since arriving in the laboratory and were not used except during pilot testing and the actual data collection. Two of the commercial swipe sensors were disassembled, so the swipe sensors and cables could be used in the PUSH and PULL designed form factors.

Figure 58 Fingerprint sensors used (from left to right): 1) Eikon swipe sensor, 2) PUSH designed sensor, 3) PULL designed sensor, and 4) TouchChip large area sensor.

3.3.7.2. <u>Computer Equipment</u>

Two computers were used for the quantitative data collection, one for the research administrator and one for the participant to interact with (Figure 57).

The research administrator computer was a Dell Optiplex GX620 with Dual 17 inch monitors. The data collection computer that the participants interacted with was a Dell Optiplex 150 with a Single 17” monitor. To minimize complexity for the participant a TRENDnet 2-port KVM Switch was used to control the data collection computer so the participant was only responsible for interacting with the fingerprint sensors and not the mouse or keyboard. For a complete listing of what software each computer ran during testing, please refer to Appendix N.

3.3.7.2.1. Research computer screen capture and user interaction video recording

Recordings of both the data collection computer’s screen and user-fingerprint sensor interaction were recorded for each visit using the researcher’s computer, which is shown in Figure 59.

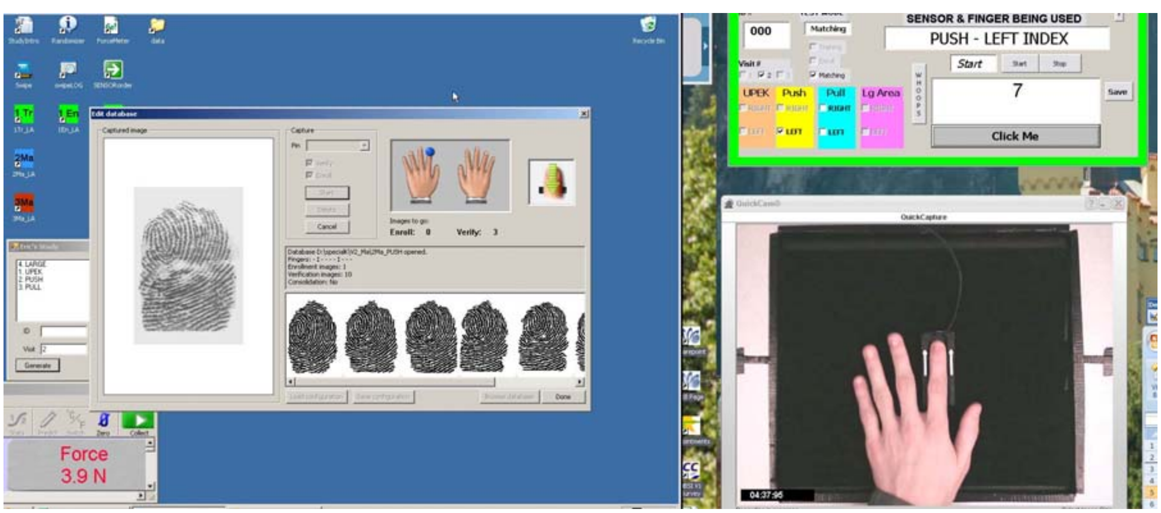


Figure 59 Screenshot of the researcher’s computer showing video recordings of the participant’s computer monitor (left), the participant’s interaction with the sensor (lower right), and the interaction counter the researcher used to count presentations (top right).

The video sources were segmented by type (Computer screen and human interaction) and visit (1, 2, and 3). Both of the video sources were used to perform the usability analysis of the devices. The usability analysis occurred in real-time after all of the data were collected. However, the author counted the number of interactions/presentations in real time using the HBSI counter (Figure 59 top right). All human interaction video sessions were stored on a computer hard drive using the Logitech Quickcam v11.5 program. All computer screen capture recordings were performed with MatchWare ScreenCorder 4.0.

3.3.7.2.2. Fingerprint Data Collection Software

Two fingerprint data collection software programs were used in the study. The same software was used in all three visits and for training, enrollment, and matching. The first was UPEK Internal DBCollection 4.5.0.19, which was used for the three swipe-based fingerprint sensors, which is shown in Figure 60. The other software tool was the UPEK TouchChip DataBase Collection 1.1.0.0, which was used for the large area sensor and is shown in Figure 61.

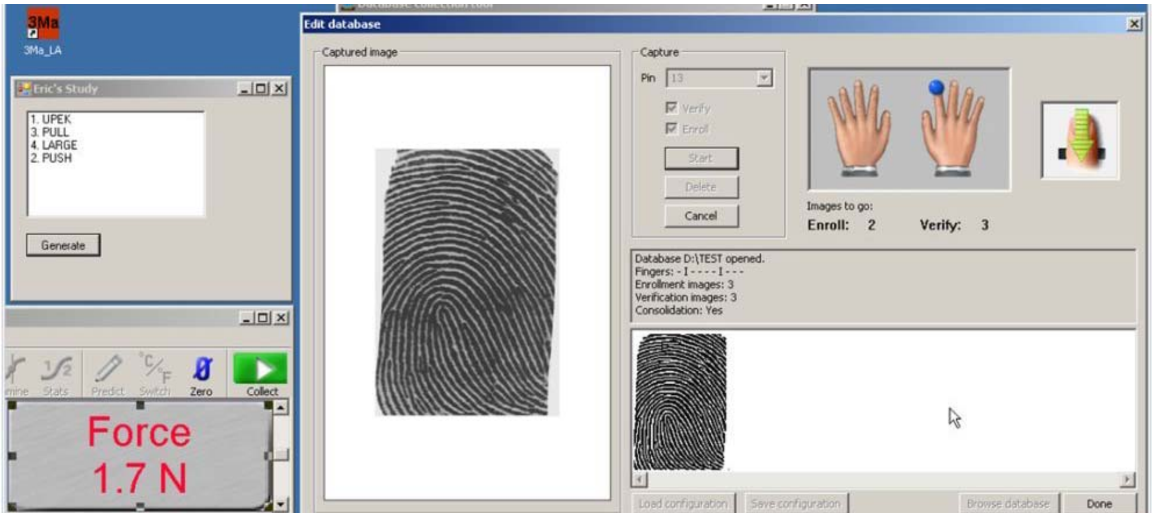


Figure 60 Screenshot of the software used for the swipe-based sensors.

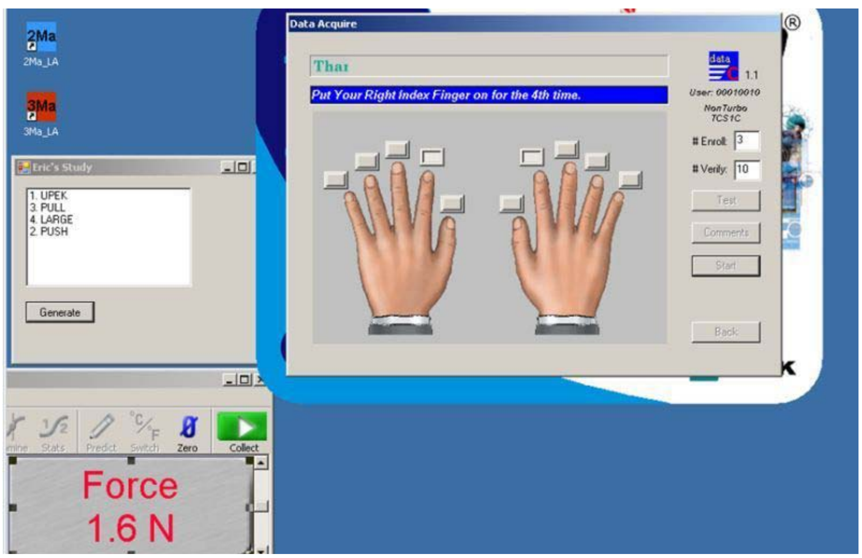


Figure 61 Screenshot of the software used for the large area sensor.

3.3.7.2.3. Anthropometric Devices

Anthropometric measurements were collected using a Hewlett-Packard ScanJet 4600 flatbed scanner. This was to ensure measurements were accurate and measured in a repeatable fashion throughout the test, so threats to internal validity could be minimized. The following measurements were taken from the scanned images using the Adobe Photoshop CS3 Comprehensive image analysis measurement toolkit:

- Hand length (Middle finger to base of the hand)
- Hand breadth (metacarpal)
- Length of Index finger
- Breadth of Index proximal interphalangeal joint (PIPJ).

To obtain the measurements from the hand scans, each image was analyzed manually using the Adobe Photoshop CS3 Comprehensive image analysis toolkit. The measurements were taken based on the dimensions discussed in section 2.8.4.2.1. Boundaries of the fingers and palms were found by inverting the hand scan image, as this process revealed clearer edges of the finger and palms. The ruler in the analysis measurement toolkit was then utilized to record each of the measurements, which were then exported to Microsoft Excel for further analysis. The entire measurement process was similar to Salvendy (1971), which was discussed in section 2.7.1.1. An example hand scan that was inverted to find the edges, with measurements is shown in Figure 62.

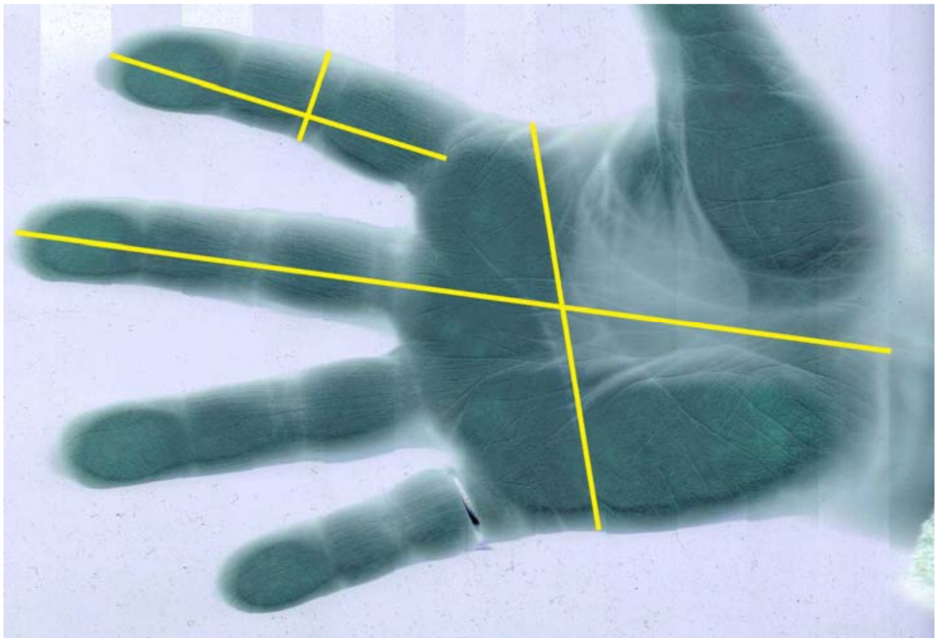


Figure 62 Inverted hand scan image with example anthropometric measurements used in this research.

The circumference of index finger Distal Interphalangeal Joint (DIPJ) was measured using the Richardson Products finger circumference gauge (Figure 63).

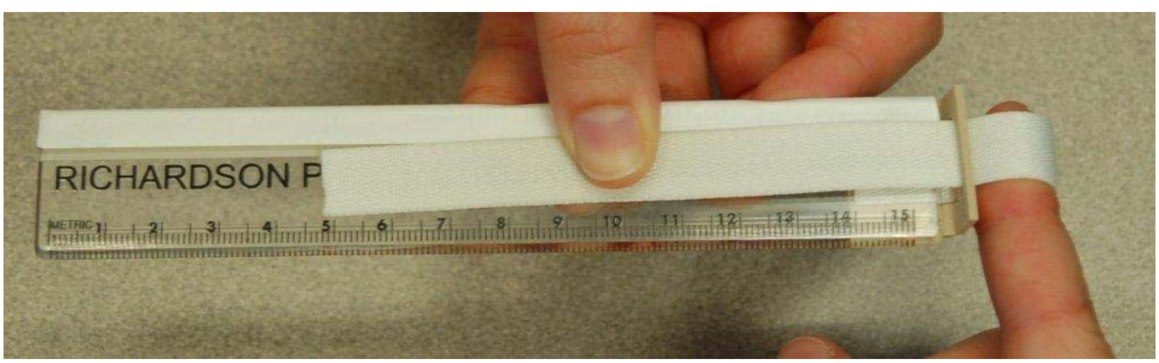


Figure 63 Richardson Products finger circumference gauge.

3.3.7.2.4. Skin Characteristic Measurement Devices

Skin characteristics of the dominant index finger were taken prior to the participants presenting their fingers to the sensor in each visit. Skin surface temperature was measured with the RayTek MiniTemp Infrared sensor. Moisture, oiliness, and elasticity were measured using the Moritex TripleSense device. Both can be seen in Figure 64.

Figure 64 Skin measurement devices: RayTek surface temperature sensor (left) and Moritex TripleSense device (right).

3.3.8. Experimental Design

Data collection occurred over three visits in a repeated-measures experimental design that took a minimum of four weeks to complete. Visits one and two were preferred to occur in consecutive weeks, but alterations were made due to appointment and participant availability. Visit three occurred with a minimum of one academic week separation between visit two. The preferred/minimal time requirements for data collection are shown in Table 20.

Table 20 Preferred/Minimal time requirements for data collection.

	Week			
	1	2	3	4
Data collection components (DCC)	Visit 1 Training Enrollment Matching 1	Visit 2 Matching 2		Visit 3 Matching 3

During each visit, each participant interacted with four fingerprint form factors, which was the independent variable in the study to determine if measurements and principles from usability, ergonomics, and biometrics can lead to improvements captured by the proposed HBSI evaluation method. The four levels of the independent variable are:

1. Commercial swipe sensor (UPEK)
2. Form Factor Design 1 (PUSH)
3. Form Factor Design 2 (PULL)
4. Commercial large area sensor (LA).

The ordering of the sensors was pseudo-random, which was controlled with a software tool developed in the BSPA Laboratory to reduce the possibility of systematic error due to expected improvement on the last device compared to the first (habituation), which could have threatened the validity of the study if it was not controlled (Zevecic, Miller, & Harburn, 2000). While the sensors were randomly ordered, participants always began with their right hand, regardless of dominant hand, due to limitations of the fingerprint collection software. The limitation of the software required images from the right hand to be collected first, followed by the left hand. This was important to adhere to because the software named the image with a marker indicating which hand and finger the image was collected from. Therefore, participants could have been more familiar with a particular device with the left hand, as the protocol always required right hand interaction first. During each visit, each participant interacted with all four sensors with two fingers unless an acquisition level FTE occurred with a particular sensor/finger combination during the enrollment data collection component of visit 1. In the case of an acquisition level FTE, the sensor/finger combination producing the acquisition level FTE was not revisited for the remaining visits. The two digits used in the study were the right and left index fingers. The general data collection protocol is shown in Table 21. During the training, enrollment, and matching data collection components, the author observed and recorded each interaction with the sensor that acquired a fingerprint image and that did not acquire an image when the participant was in contact with the sensor.

Table 21 General data collection test protocol.

Visit	Interaction Data collection component	Sensor			
		UPEK	PUSH	PULL	Large Area
1	Training	4/15	4/15	4/15	4/15
1	Enrollment	10/30	10/30	10/30	10/30
1	Matching	10/30	10/30	10/30	10/30
2	Matching	10/30	10/30	10/30	10/30
3	Matching	10/30	10/30	10/30	10/30

Key: # of successful interactions desired / # presentations allowed per sensor

Information about the number of presentations required to complete the interaction data collection component during a visit was counted by the author, recorded through screen capture and a video camera, and automatically logged to a file for later analysis. These three measurements of the interaction activity allowed for triangulation techniques to be used to ensure errors were not made during analysis.

In addition to the items listed above; the user task time, number of user-interaction attempt errors, and number of assists were recorded for each participant by sensor/visit. Data collection targeted between 75 to 100 participants, which was in-line with previous biometric usability evaluations (Kukula & Elliott, 2006; Theofanos, Orandi, Micheals, Stanton, & Zhang, 2006; Theofanos, Stanton, Orandi, Micheals, & Zhang, 2007). The final number of participants in this study was 85.

3.3.8.1. Testing Procedure

The testing procedure for the quantitative data collection effort followed three main procedures: the daily startup process (Appendix I), the HBSI data collection process (Appendix J), and the daily/weekly backup and shutdown process (Appendix K). The following sections will further describe the HBSI data collection process.

3.3.8.1.1. Modifications from the Pilot Test

Prior to beginning the actual data collection, a two person pilot test was conducted. After the second individual completed the test, no changes were made to the setup or procedures, thus was finalized and data collection began.

The largest change from the pilot test involved the participant disengagement from the fingerprint sensor. Originally, the protocol called for participants to interact with a computer mouse and perform a click task with the right hand for right index fingerprint presentations, and the left hand for left index fingerprint presentations. However observing the first individual going through the pilot, revealed that the mouse task was burdensome and complicated for the participant to complete as well as interact with the fingerprint sensors. Thus the setup was modified so the author controlled the participant computer. Additionally, instead of performing the mouse click task, black tape was added to each side of the force plate, and participants were asked to tap their finger between each presentation to the sensor.

3.3.8.1.2. Visit 1: Protocol Introduction and Training

During the first half of each participant's first visit, the study was introduced, demographic and anthropometric data were collected, and the consent form was signed. The protocol introduction and training procedure is outlined in Figure 65.

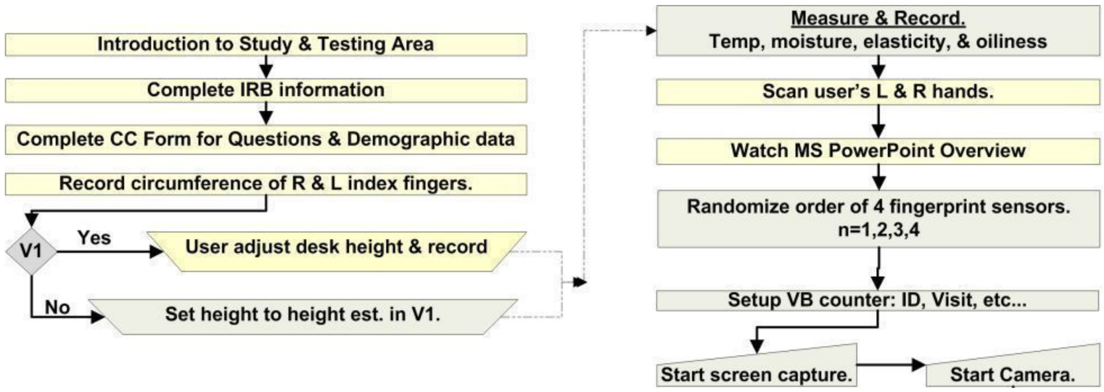


Figure 65 Protocol introduction and training procedure.

After completing the consent form, participants were familiarized with the overall testing area (Figure 57) that consisted of the researcher and participant workstations. Figure 66 shows a front view of the participant workstation that includes a computer, four fingerprint sensors, a flat bed scanner, force plate, and video camera.

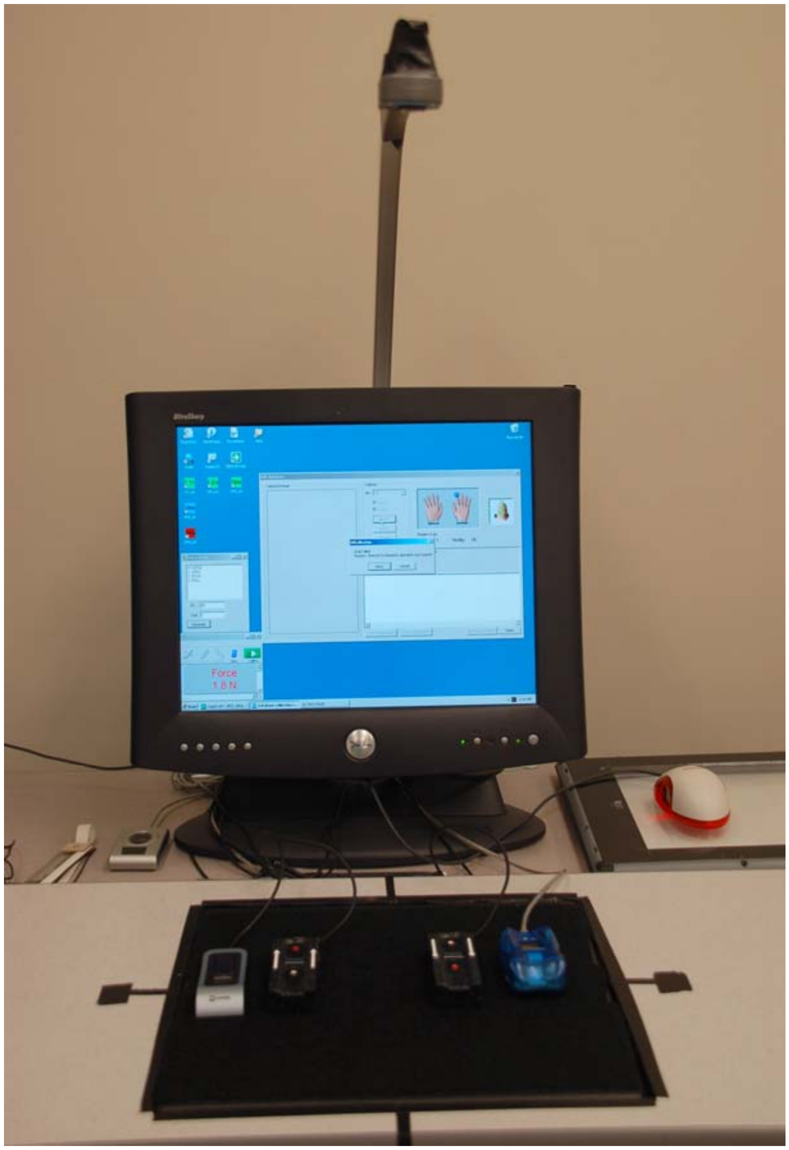


Figure 66 Front view of data collection computer that participants interacted with.

Video that was collected of the participants' interaction with the fingerprint sensors only included the hands to maintain human subject confidentiality requirements (Figure 67 and Figure 68). The defined area, which was colored black, was established within the experimental area to allow for the field of view of the camera to record the interaction and provide feedback to where participants had to interact with the fingerprint sensors. The square area, which was a Vernier force plate, was overlaid with soft Velcro, enabled participants to fasten the devices in such a manner that was most comfortable for them. The Velcro also helped maintain sensor stability. This area is shown in Figure 67. Participants were also instructed that they could place the sensor wherever they wanted as long as it was on the black surface. After placing the sensor on the surface, the participants were asked to remove their hand from the surface so the Vernier force sensor could be tared. Lastly, participants were instructed that after each interaction, swipe or placement, with the sensors to remove their hand from the sensor and touch the square black tape on the right side for interactions with the right hand and left side for interactions with the left hand. This was to ensure participants disengaged briefly from the sensor between each presentation to the sensor. This was important for two reasons. First, this research was investigating the interaction of the human and sensor and if the participant continuously interacted with the sensor without short breaks or disengagements, the measurements would have been corrupted and not valid. Therefore, the short break from the tap between interactions allowed for unique and independent presentations that simulated a real-world implementation of fingerprint recognition, as opposed to continuous and rhythmic presentations that can occur during data collection. Secondly, the short break from the tap allowed the author time to analyze each presentation to ensure data analysis errors were minimize. An example of the sensor interaction and disengagement that was repeated after each swipe and placement is shown in Figure 68. After these instructions were given, any remaining questions regarding the experimental setup or fingerprint sensors were answered.

Figure 67 Experimental area that the video camera recorded showing disengagement markers.

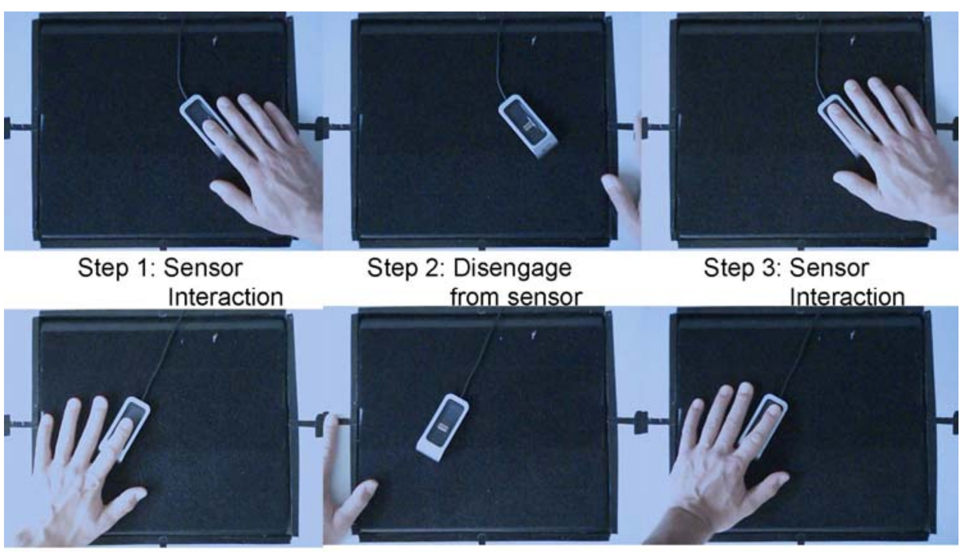


Figure 68 Sensor interaction and disengagement, or tapping, process that was followed by participants with each sensor for the right (top) and left (bottom) hands.

Next, a demographic questionnaire (Appendix L) was completed. The participant was then asked to adjust the height of the desk to the working height of their choice. This value was recorded and was set to the same height before each subsequent visit to limit variability within the subject. Next, one scan of each hand was taken using the HP ScanJet 4600 scanner at 300 dpi to obtain all the anthropometric measurements except finger circumference, which was taken for both right and left index finger using the finger circumference gauge (see section 3.3.7.2.2). Lastly, the participant's dominant index finger was measured for surface temperature, moisture, elasticity, and oiliness (Figure 64). At this point, the author initiated the MatchWare ScreenCorder 4.0 screen capture software to record the visual display of the data collection computer. The Logitech Quickcam v11.5 was then started to record the interaction between the participant and the fingerprint sensors. Next, the subject began learning how to use the fingerprint sensors and software in the training data collection component that simulated what the data collection process looked like. Training occurred for both index fingers and will be further discussed in the next section.

3.3.8.1.3. Training data collection component

The training data collection component acclimated participants to the testing procedure, including: interacting with the fingerprint sensors, appearance of the software, and potential questions the author could have asked throughout the three visits. The procedures for the training phase are shown in Figure 69. Each participant had up to 15 presentations to acquire four images that captured with both the right and left index fingers. These interactions served as a baseline measure to determine if additional training or other intervention was needed prior to beginning the enrollment and matching data collection components. FTA calculations were conducted for training presentations that failed to produce images. Assistance was provided if the participant performed four presentations without a successful image capture. Assistance throughout the study had two forms: verbal instructions or physical intervention. The same assistance protocol was followed for training, enrollment, and matching.

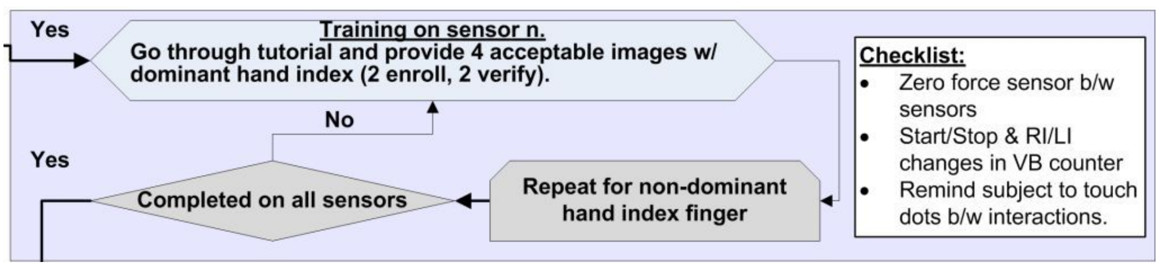


Figure 69 Training procedure for the 4 fingerprint sensors.

3.3.8.1.4. Enrollment data collection component

Each user had one attempt to enroll in each sensor, which consisted of 30 presentations. Enrollment was deemed successful if 10 images were acquired. In most commercial fingerprint software applications enrollment typically requiring three to five presentations. 10 successful presentations were used to collect more data and analyze if participants improved their interaction in terms of the HBSI ergonomics and image quality measures and performance over time. The enrollment procedure is shown in Figure 70.

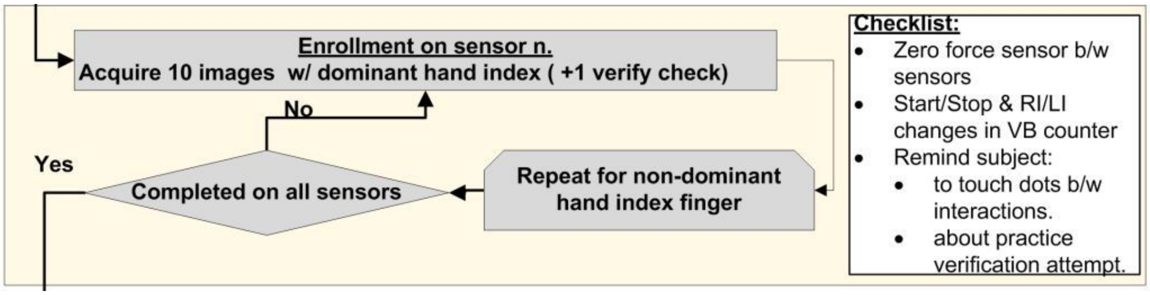


Figure 70 Enrollment procedure for the 4 fingerprint sensors.

Both FTA and FTE calculations were conducted for the enrollment data collection component. FTA classifications were conducted in the same manner as in training. If a participant failed to produce sufficient images after 30 allotted presentations in the provided attempt with a given sensor, it was recorded as a failure to enroll (FTE). If an acquisition level FTE was registered, the participant was not allowed to use that particular sensor with the finger that failed to enroll for any of the matching visits.

3.3.8.1.5. Matching data collection component

The matching data collection component utilized the same software applications that were used during training and enrollment. Matching was the only data collection component that occurred each visit. Matching required each participant to successfully interact with each fingerprint sensor 10 times with each finger. The protocol allowed for up to 30 presentations with each finger. Each presentation that failed to produce an acceptable image was recorded as an FTA. If a participant did not achieve 10 successful image captures within the 30 allotted presentations, subjects were asked to stop and move onto the next task, however they were required to interact with that particular combination during the next matching visit. The visit 1 procedure is shown in Figure 71 and the procedure for visits 2 and 3 are shown in Figure 72. Upon completion of visit 3, each participant was asked to complete the HBSI post study usability questionnaire (Appendix A).

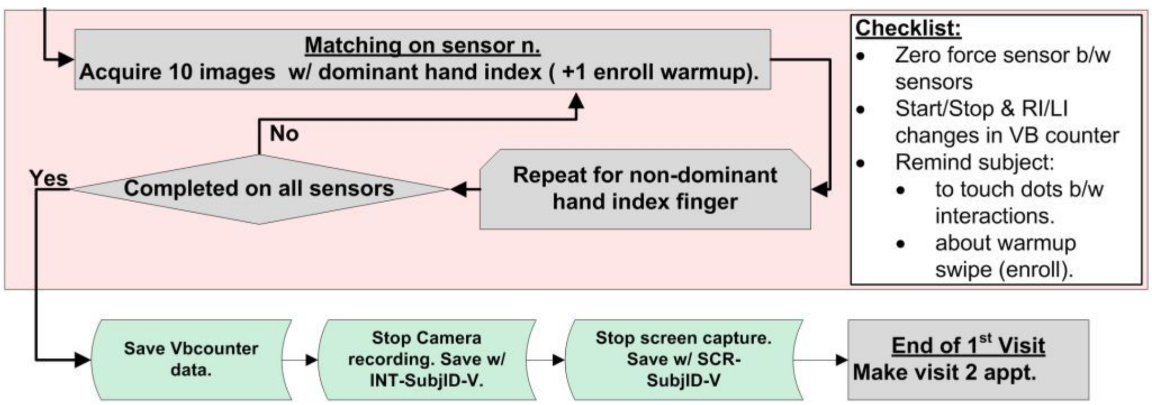


Figure 71 Matching visit 1 procedure for the 4 fingerprint sensors.

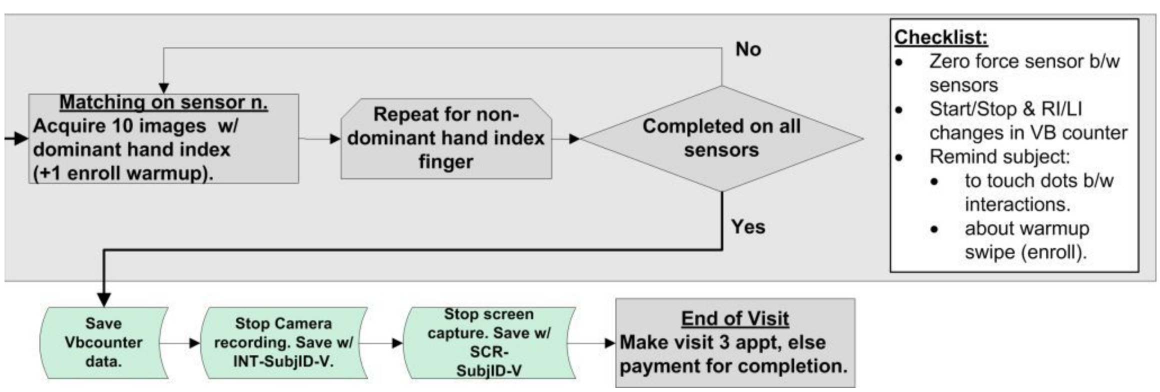


Figure 72 Matching visit 2-3 procedure for the 4 fingerprint sensors.

3.3.9. User Interaction Data Analysis

Once all the data were collected, data analysis occurred with Noldus Information Technology's Observer XT 7.0 software package with two video modules. This software suite allowed the author to create the coding scheme based upon the tasks defined in the testing protocol.

The coding scheme was based upon the actions, behaviors, and system results encountered during data collection. The original coding scheme included metrics for task time, sensor position, FTA analysis, and assists, but the final coding scheme was created prior to starting the usability analysis and derived from the subject specific observation documents taken for each participant. Appendix L contains an example observation document for one participant. This ensured all observed behaviors could be included during the analysis. Finalizing the coding scheme prior to beginning the analysis, as well as using the same researcher to code the data, enabled all the data to be analyzed against the same criteria by the same individual, limiting threats to internal validity. The coding scheme used in the usability analysis can be seen in the following tables:

- Table 22 - Training, enrollment, and matching v1, 2, and 3 data collection component selection:
- Table 23 - Finger selection:
- Table 24 and 25 - FTA analysis,
- Table 26 - Assistance:
- Table 27 - Other behavior
- Table 28 - Sensor position and location

Table 22 Usability coding scheme for data collection component selection.

Time	Code
Training	e
Enrollment	r
Matching v1	t
Matching v2	y
Matching v3	u

Table 23 Usability coding scheme for finger selection.

	Finger Code			
	UPEK	PUSH	PULL	LA
RI	1	2	3	4
LI	5	6	7	8

Table 24 Usability coding scheme behaviors for FTA analysis.

Behavior Name	Start	Modifiers
RI Acceptable Conformant	*	
LI Acceptable Conformant	/	
RI Unacceptable Conformant	9	FTA
LI Unacceptable Conformant	8	FTA
RI Acceptable Non-Conformant	6	Acceptable non-conformant
LI Acceptable Non-Conformant	5	Acceptable non-conformant
RI Unacceptable Non-Conformant	3	
LI Unacceptable Non-Conformant	2	

Table 25 Usability coding scheme modifiers for FTA analysis.

Modifier Name	Start
FTA	i
Too Fast	f
Too Short	h
Center & Press Harder	j
Too Skewed	k
Wrong Movement (backwards)	z
Too Strange	x
Acceptable non-conformant	M
wrong finger	w
wrong direction	r
other	o

Table 26 Usability coding scheme assistance instructions.

Test Admin Instructions	Code
Flatten hand / open hand	a1
Press harder	a2
How to use – direction/placement	a3
Slow down	a4
Keep fingers straight (no curl/flick)	a5
alignment – start position	a6
Faster	a7
Physical Intervention	a8
Alignment – Center finger over sensor	a9
User Fingertip pad	a0
Software – LA	a-

Table 27 Usability coding scheme for other behaviors.

Other User Behavior	Code
Used 2 hands to swipe	o1
Held sensor w/ off hand	o2
Participant rushing through visit	o3
Moved sensor during session	o4
Behavior_Other_GOOD	o5
Behavior_Other_BAD	o6
Behavior_TIMER	oo

Table 28 Usability coding scheme for sensor position on the force plate.

Sensor Angle	
Vertical (0 degree)	w5
Left Tilt MINOR (90-135)	w4
Right Tilt MINOR (90-45)	w6
Left Tilt MAJOR (135-180)	w1
Right Tilt MAJOR (45-0)	w3
Sensor Location	
Center/Middle	q5
Lower Right	q3
Upper Left	q7
Upper Right Quadrant	q9
Lower Left	q1
Vertical Top	q8
Vertical Bottom	q2
Horizontal Left	q4
Horizontal Right	q6

Once all the data were collected the author analyzed each video for particular actions, behaviors, and biometric system results and documented the occurrence of each. Thus, each of the defined variables discussed earlier: task time for training, enrollment, and each matching visit, number of acquisition and enrollment errors, and number of assists were documented and analyzed. Figure 73 shows a screenshot of the Noldus software displaying the event log, partial coding scheme, and two video modules.

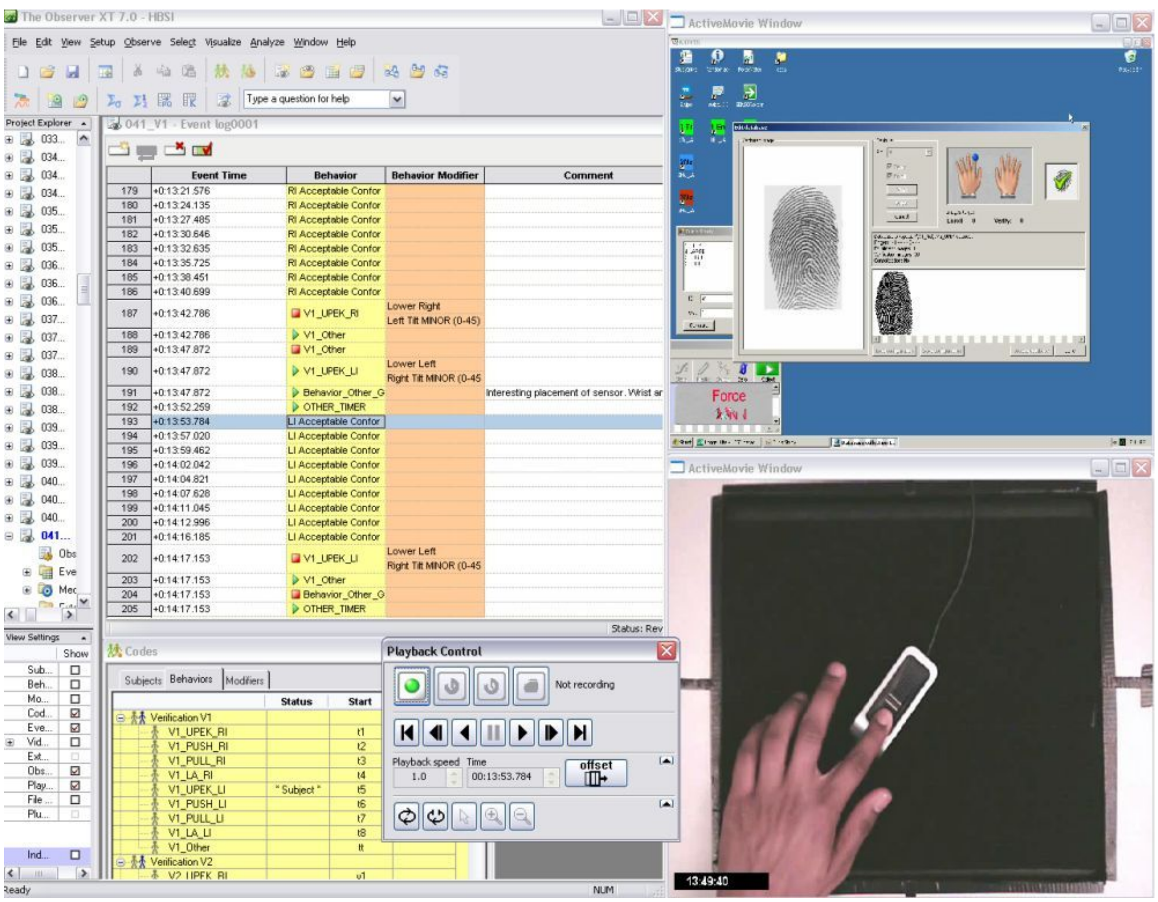


Figure 73 Usability software used to code task time, interactions, and assists in real time using the two video modules.

3.4. Threats to Internal Validity

Internal validity was defined for this study as the extent the experimental design allowed for the form factor type to impact usability, image quality/ergonomics, and biometric performance. In any experimental design, there are a number of threats that can arise in research that may impact internal validity, namely instrumentation, history effects, testing effects, statistical or regression-toward-the-mean, mortality, maturation, and selection bias (Asher & Lauer, 1988; Sekaran, 2003). The following sections discuss how each of potential threats were accounted for or acknowledged.

Instrumentation threats were minimal as the measuring instruments, devices, and testing area were unchanged for all participants for the duration of the study. If anything out of the ordinary was observed, it was noted. In terms of the qualitative interviews, internal validity was kept to a minimum due to the interview question guide sheets, which ensured that all participants responded to the same questions. In addition only one researcher coded, transcribed, and administered the testing, removing the inter-rater effect of multiple researchers.

Mortality could not be eliminated from this research. According to the Committee on the Use of Human Research Subjects at Purdue University, participants must voluntarily consent to partake in any research. To account for mortality, participants withdrawing from the study were documented.

Maturation, or habituation, occurred as participants became more acclimated to the fingerprint sensors, software, and testing protocol. To account for habituation to the devices, participants were asked if they have previously had experience with fingerprint recognition during the initial visit. In addition, the ordering of the sensors was pseudo-random, meaning the order was different each visit. This mitigated order effects as well as one sensor outperforming another due to its position in usage.

Selection bias was a major concern in this research. Over 90% of the participants interacting with the fingerprint sensors had prior experience with fingerprint sensors, with a majority using the UPEK sensor before. This could negatively bias the results of the usability survey as their preference may already be made before interacting with the alternative devices. Furthermore, participants who have used fingerprint recognition prior to this study, may interact at a higher level than those who have not used biometrics before. Selection bias was accounted for with the demographic and background analysis.

Lastly, statistical regression could have impacted the internal validity of the study. Individuals who perform very well or badly can threaten the validity of the study. In biometrics research the “outliers” are of extreme interest, as a majority of individuals can successfully interact with biometric devices. Statistical regression was accounted for in the analysis section by providing descriptive statistics and plots of the data to provide further information on the results of the tests.

3.5. Threats to External Validity

During the process of an evaluation, many threats to the generalizability of the research results to other groups or populations can occur, which is known as external validity (Asher & Lauer, 1988). In any scenario based lab research, there will be threats to generalizability, due to the assumptions and delimitations that are made within the scope of the particular study. Please see sections 1.8 and 1.9 for the assumptions and delimitations made in this research. Furthermore, the HBSI evaluation method was stated to specifically be for physical interactive biometrics, meaning transfer to imaging based biometrics, such as iris or face recognition would likely be problematic in the evaluation method's current state. Additionally, to not predispose participants to the usability questionnaire they completed in visit 3, a pre-test was not given, as this would bias the results for a particular response. In addition, participants were not informed that the author designed the alternative form factors until after the participant completed the entire study, as this would have compromised the results of the individual, as they may have felt the need to rank the sensors the author created above the others.

CHAPTER 4. DATA AND ANALYSIS

This study had four objectives: (a) review the literature to determine what influences the interaction of humans and biometric devices, (b) develop a conceptual model based on previous research, (c) design two alternative swipe fingerprint sensors, and (d) evaluate the commercially available and alternative form factor devices in a comparative performance evaluation using the HBSI evaluation method.

This chapter presents the data and analyses from each of the three parts in the following order: 1) qualitative interviews, 2) design and fabrication of the alternative fingerprint form factors, and 3) quantitative performance evaluation.

The first phase was the qualitative component, which consisted of a single visit interview of fingerprint users, ergonomic experts, and non-users to collect data and gather interaction feedback from their use of a commercial swipe-based fingerprint sensor to aid in the design of the two alternative swipe-based fingerprint sensors.

The second phase was the design and fabrication of the two form factor devices. The results from the qualitative study, as well as principles in the usability, ergonomic, and biometric literature were used to create the swipe-based fingerprint form factors.

The third phase of this research evaluated the two designed swipe-fingerprint sensors (PUSH and PULL) to a commercial swipe fingerprint sensor (UPEK) and a baseline large area (LA) sensor using the HBSI evaluation method.

4.1. Phase 1: Qualitative Study

The qualitative component of this study consisted of 22 interviews. The use of qualitative interviews allowed the author to collect data rich in details to gain an understanding of the human element for designing a swipe-based fingerprint form factor. Two qualitative research and evaluation methods, phenomenology and systems theory were followed to collect and analyze the data from interviews of biometric users, non-users, and ergonomic experts. The goal of the interviews and analysis were designed to provide design guidelines for the two alternative swipe-based sensors from the user perspective. The interviews were based around the central question:

> *What criteria do users, non-users, and ergonomic experts believe should be included in the design of a swipe-based fingerprint sensor form factor to make it more usable, comfortable, and efficient for users?*

The qualitative results are discussed in four sections: volunteer crew, data collection, data analysis, and key findings for design and fabrication.

4.1.1. Volunteer Crew for Phase 1

The volunteer crew for the qualitative study consisted of 22 individuals. Fourteen were fingerprint users, meaning they had participated in at least one fingerprint study in the Biometric Standards, Performance, and Assurance Laboratory involving swipe-based fingerprint sensors. Four individuals were classified as ergonomic experts. Of the four individuals, one was a faculty member, two were doctoral students, and one was pursuing a Master of Science degree in ergonomics or usability. Half of the 22 participants were less than 30 years of age, with 59.1% being female. 77.3% of the participants self-reported their ethnicity as White, 9.1% self-reported Asian, 4.5% Hispanic and Black, and one participant reported Other. Participant demographics are shown in Figure 74. Also, over 81% of the participants had used some form of fingerprint recognition prior to this study, which is broken down by technology type in Figure 75.

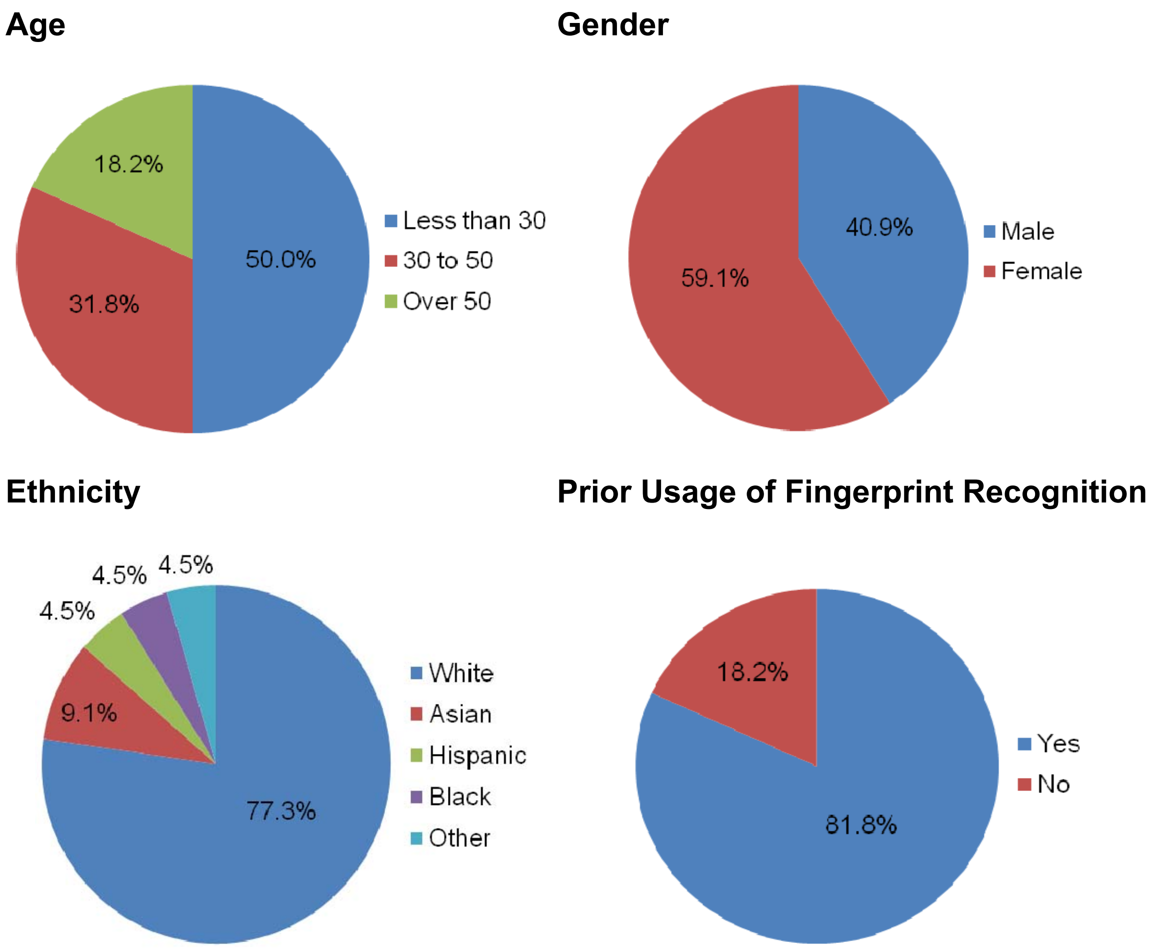


Figure 74 Participant age, gender, ethnicity and prior fingerprint usage demographic information.

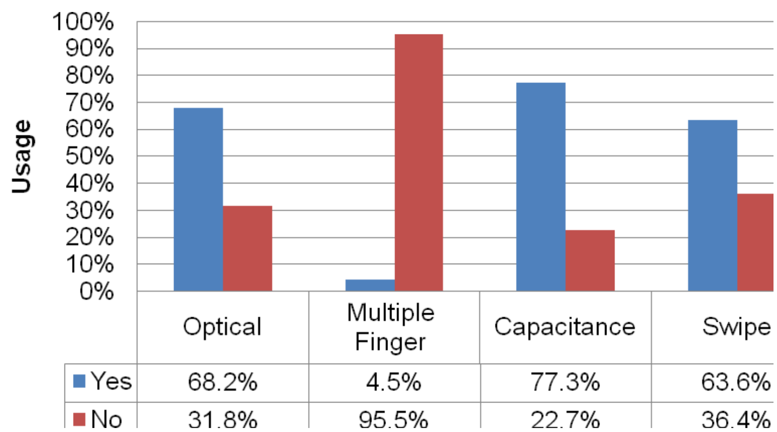


Figure 75 Prior fingerprint usage by technology.

4.1.2. Data Analysis for Phase 1

Once the data were collected and transcribed, it was analyzed using inductive data analysis. As discussed in the qualitative methodology section, inductive analysis involves discovering patterns, themes, and categories in the data (Patton, 2002). During data analysis, the author created a code book of common themes and categories that was used to discover possible connections in the data. Approximately four iterations occurred to create the final design categories for the swipe-based fingerprint sensors. The following three sections describe the analysis strategies that were taken to create the final design from the interviews.

4.1.2.1. Initial Data Investigation

The initial data analysis enabled the author to become immersed in the data in order to better understand participant responses. In order to do this, each interview answer was grouped within the three interview types: fingerprint recognition users, non-users, and ergonomic experts. Weft QDA v1.0.1 (Figure 76) was used to perform a textual analysis on the transcripts and create the initial coding scheme, which can be found in Appendices O – Q for each of the three interview groups. Each of the three schemes were created by the author using the software. Once the initial coding was complete, the output for each group was exported to Microsoft® Excel®. Next, each item was printed and organized into condensed themes and combined amongst the three groups. Once each printed item was listed in a category or theme, reanalysis of the data occurred to ensure each response was under the appropriate preliminary theme.

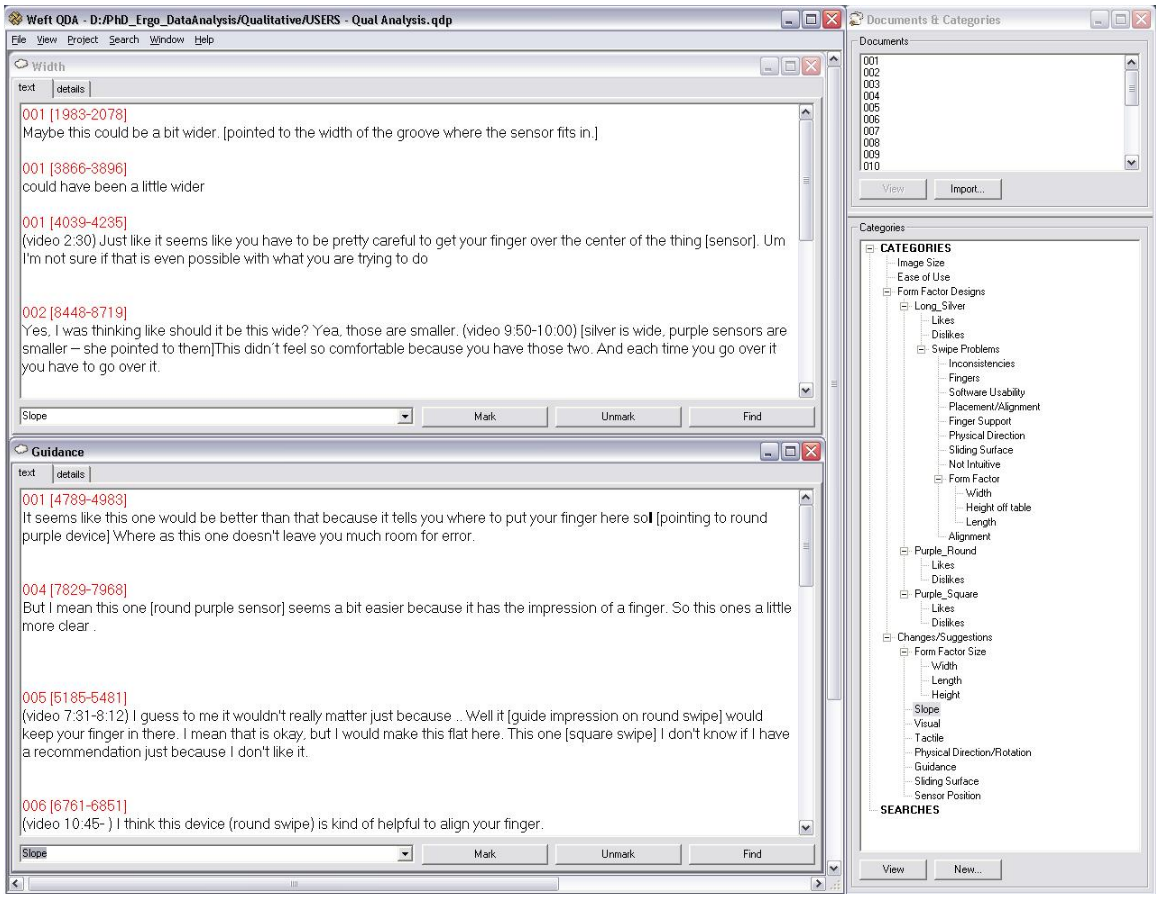


Figure 76 Screenshot of Weft QDA software that performed the initial data investigation. Image shows initial coding structure for users [Appendix O](right), participant statements about the width of the sensor (top), and participant statements regarding guidance (bottom).

4.1.2.2. Secondary and Tertiary Data Investigations

Next, the initial coding bins were examined to see if relationships or over arching themes existed within the initial coding structure. Once this was complete, the data were reanalyzed by more specific categories and themes. This process was repeated to continue developing the natural patterns and themes in the data.

4.1.2.3. Final Data Investigation

Following the third pass through the data, a fourth analysis was completed to further cleanse the data. After this investigation, the themes or principal design components were readily apparent with only slight modifications occurring from the third analysis, thus the coding structure was considered complete. The final design component structure from the qualitative analysis is shown in Figure 77. Appendix R contains the qualitative results from the interviews sorted by the principal design components shown in Figure 77.

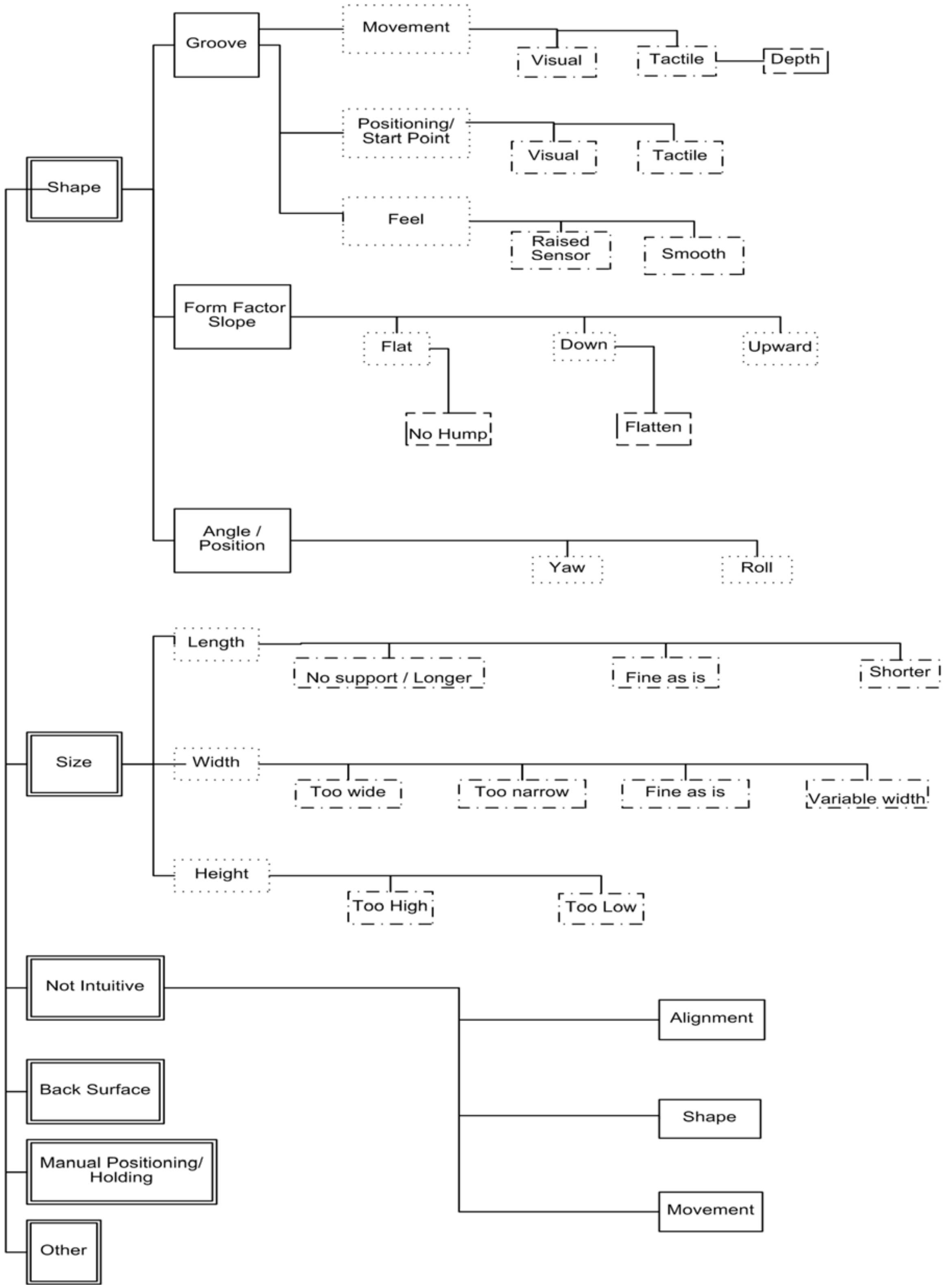


Figure 77 Principal design components from the qualitative data.

To provide the reader a better understanding of the data collected, excerpts from the final data (Appendix R) regarding design issues are presented below.

Participant 33 stated the following with respect to designing an alternative device:

> Well I might add some sense of this guiding or indention here [guide on round swipe] on something like this. I like that this is sleek and a little lower [pointing to black part of long silver swipe]. This [round swipe] is also cold to the touch [but that is due to the materials used]. The sense of starting and stopping [pointed to round swipe finger impression guide], so this might be helpful (Appendix R, 033 [6001-6418]).

Participant 13 discussed providing more guidance:

> [referencing the round swipe] It is just easier. I think it gives you a better place to put the finger. It is easier to control factor for lack of better word. This one [long silver swipe] as I said but going across the sensor is a lot smoother. Maybe adjust it because I don't know as I said those are sticking up. But the design of it [round swipe], I like better, the going across the sensor I like better here [long silver swipe] (Appendix R, 013 [6946-7401]).

Participant 14 stated the following in terms of designing a device:

> I would take this device [round swipe] here and superimpose it on top of this device [long silver swipe], so that there is a little bit of a angled sides in the beginning. There is a little bit but a little more upward channel to keep your finger in a straight path through the sensor (Appendix R, 014 [5107-5410]).

Participant 31 stated the following about device usability and comfort:

> Yea, I think the design of this one [round swipe] it tells you and guides you with the two sides coming up. To me it tells me like “that is where you put your finger” [places finger down correctly on the round swipe]. It is telling you where to finger in that space. That is why this is my favorite it terms of design and being comfortable (Appendix R, 031 [7438-7800]).

Participant 20 stated the following about the shape of swipe fingerprint devices:

> I liked this one [round swipe] for the placement. I liked this one [long silver swipe] for the shaping of the finger, the concave feel. Like this one [round swipe] is pretty flat and that one [long silver swipe] one has, you know a little bit more. But of the three I probably would have used this one [round swipe], meaning easiest (Appendix R, 020 [8143-8496]).

Participant 30 stated the following about designing a form factor:

> Well design wise I prefer this one [long silver swipe]. I like how this one [round swipe] fits. If this part [round swipe finger guide] could be incorporated into this [long silver swipe] to cradle my finger I probably would like this one better than any of them. This one [round swipe] is kind of cold, but does fit my finger better. I suppose you have to look at this from a viewpoint that several people are using it so it doesn't matter. You can't just customize it to my hands (Appendix R, 030 [6071-6574]).

4.1.3. Results for Design and Fabrication

From the final data discussed in section 4.1.2.3, a frequency analysis (Table 29) was conducted to assess the coded responses of the interviewed individuals. From the qualitative interview results, the items with the highest frequency were considered in the design, but ergonomic, biometric, and manufacturing constraints were also taken into account. The frequency analysis reveals that the highest percentage of participant comments (17.5%) discussed the shape of the form factor and how the design should provide tactile assistance in performing the swipe. The second highest ranked component (13.1%) participants felt should be included in the design is the ability to feel where one should start and stop the swiping task. The next two highest ranked components dealt with visual feedback the form factor should provide. The remaining design components are shown in Table 29.

Table 29 Final qualitative data results used to create the form factor designs.

Description			Code	Frequency	Percentage
Shape	***Movement***	***Visual***	***GMV***	**15**	**5.6%**
		Tactile	***GMT***	**47**	**17.5%**
		Depth	***GMTD***	**14**	**5.2%**
	Start/Stop	***Visual***	***GSV***	**22**	**8.2%**
		Tactile	***GST***	**35**	**13.1%**
	Smooth		GSm	2	0.7%
	Raised Sensor		GR	6	2.2%
	Roll Angle		AR	3	1.1%
	Yaw Angle		AY	4	1.5%
	Slope	Flat	SF	4	1.5%
		No Hump	SFN	5	1.9%
		Up	SU	6	2.2%
		Down	***SD***	**13**	**4.9%**
		Flatter	***SDF***	**9**	**3.4%**
Size	Length	Too Long	SLS	7	2.6%
		Fine as is	SLF	2	0.7%
		Too short	SLL	12	4.5%
	Width	Variable	SWV	1	0.4%
		Fine as is	SWF	1	0.4%
		Too narrow	SWN	6	2.2%
		Too wide	SWW	6	2.2%
	Height	Too low	SHL	7	2.6%
		Too high	SHH	1	0.4%
Manual Holding / Positioning			MHP	6	2.2%
Back Surface			***BS***	**10**	**3.7%**
Not Intuitive	Shape		NIS	4	1.5%
	Swipe movement		NIM	4	1.5%
	Align Start-Stop		***NIA***	**11**	**4.1%**
Other			OT	5	1.9%
Total count				268	

4.2. Phase 2: Design and Fabrication

The design of the two form factors was based upon the results of the qualitative analysis (Phase 1) and guided by concepts and constraints of ergonomics, usability, and biometrics. A large number of the responses (Appendix R) discussed the strengths of the long silver swipe sensor (UPEK) and the round swipe sensor, which are shown along with the square swipe sensor in Figure 55. A response by participant 14 regarding design concerns for the swipe fingerprint sensor form factor summarizes the statement perfectly.

> I would take this device [round swipe] here and superimpose it on top of this device [long silver swipe], so that there is a little bit of a angled sides in the beginning. There is a little bit but a little more upward channel to keep your finger in a straight path through the sensor.

In addition, a number of participants also wanted more visual and tactile guidance on where to start and stop the swipe motion and in what direction. A response by participant 31 best summarizes the guidance design component:

> Yea, I think the design of this one [round swipe] it tells you and guides you with the two sides coming up. To me it tells me like “that is where you put your finger” [places finger down correctly on the round swipe]. It is telling you where to finger in that space. That is why this is my favorite it terms of design and being comfortable.

Combining the frequency analysis and the participant responses in full context, the following list of criteria were used in the design:

1. Start and stop cues: visual and tactile,

2. Movement and alignment cues: visual and tactile, and
3. Ability to immobilize the device during interaction.

Next, three-dimensional modeling software was used to create the form factor designs. In the next two sections each of the two form factors will be discussed, followed by more information regarding design and manufacturing steps and limitations that were encountered.

4.2.1. Pull form factor design

The pull form factor was designed to combine the acceptable features of the round swipe sensor and long silver swipe sensor that were discussed above by participant 14 during the interviews. Figure 78 shows three separate views of the pull form factor, whereas Figure 79 shows the final assembly of the two halves and a top view of the actual fabricated device.

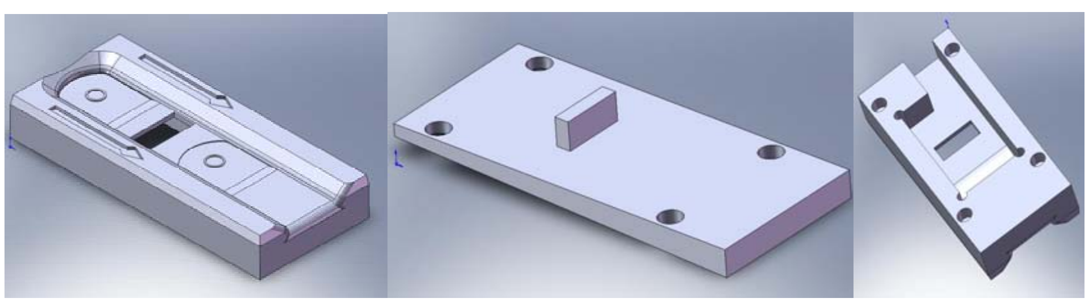


Figure 78 Top half (left), bottom half (middle), and reverse side of the top half (right) views of the CAD designed pull form factor.

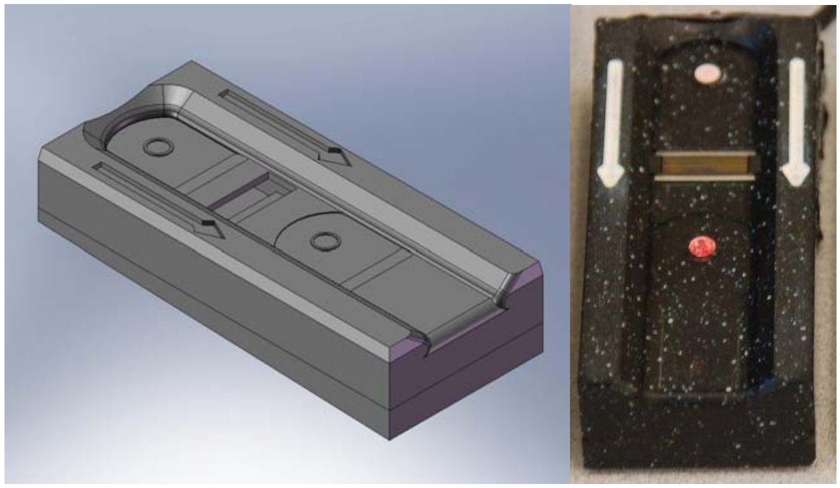


Figure 79 Final CAD model (left) and image (right) of the pull form factor.

4.2.2. Push form factor design

Many authors have suggested pushing and pulling as an occupational risk factor for musculoskeletal disorders (Badger, 1981; Clemmer, Mohr, & Mercer, 1991; Damkot, Pope, Lord, & Frymoyer, 1984; Damlund, Goth, Hasle, & Munk, 1986; Frymoyer et al., 1980; Garg & Moore, 1992; Kelsey, Golden, & Mundt, 1990; Klein, Jensen, & Sanderson, 1984; Nadeau & Gagnon, 1996; Pope, 1989; Riihimäki, 1991; Snook, 1978). Hoozeman, van der Beek, Frings-Dresen, van Dijk, and van der Woude (1998) derived the definition of pushing and pulling from Martin and Chaffin (1972) and Baril-Gringas and Lortie (1995) as “the exertion of a (hand) force, of which the direction of the major component of the resultant force is horizontal, by someone on another object or person” (p. 758). Clarifying further a pushing task involves the (hand) force being directed away from the body, while the pulling force is directed toward the body.

While much research has been performed on pushing and pulling with industrial workers and manual material handling tasks, the results have been inconsistent and unclear (Todd, 2005). Yet for manual handling tasks the Australian Safety and Compensation Council's *National Code of Practice for the Prevention of Musculoskeletal Disorders from Performing Manual Tasks at Work* (2007) states:

> Pushing loads is preferable to pulling because it involves less work by the muscles of the lower back, allows maximum use of body weight, less awkward postures and generally allows a forward facing posture to be adopted, providing better vision in the direction of travel (p. 78).

In a separate study, Thatcher, James, and Todd (2005) conducted research which indicated participants preferred a push task over a pull task, as they found it most comfortable.

With regards to swipe fingerprint devices, the task puts little stress on the body as opposed to a manual handling task. However, at the time of writing, all commercial swipe-based fingerprint sensors require a pulling or swiping motion. It is understood there are certain errors that are attributable to a swipe sensor, as the user is required to "sweep" their finger across it. This sweeping (pulling) motion requires smaller muscle groups and tendons to act to complete the task. However, is it possible to minimize these errors by introducing a push-based swipe sensor? This research question coupled with the ergonomics literature regarding pushing versus pulling led to the design of the push sensor.

The push form factor was designed similarly to the pull sensor, by combining the acceptable features of the round and long silver swipe sensors.

Figure 80 shows three separate views of the push form factor, whereas Figure 81 shows the final assembly of the two halves and a top view of the actual fabricated push device.

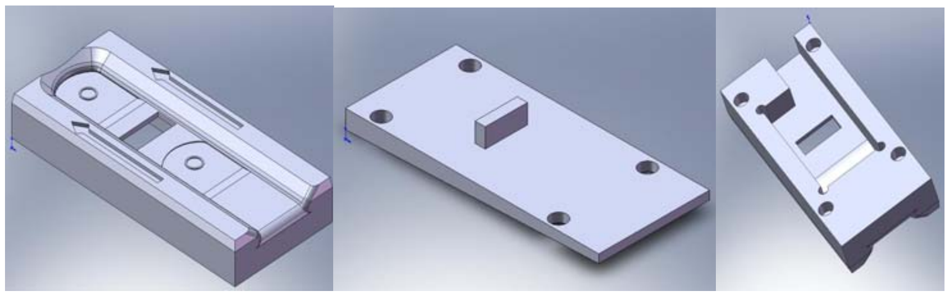


Figure 80 Top half (left), bottom half (middle), and reverse side of the top half (right) views of the CAD designed push form factor.

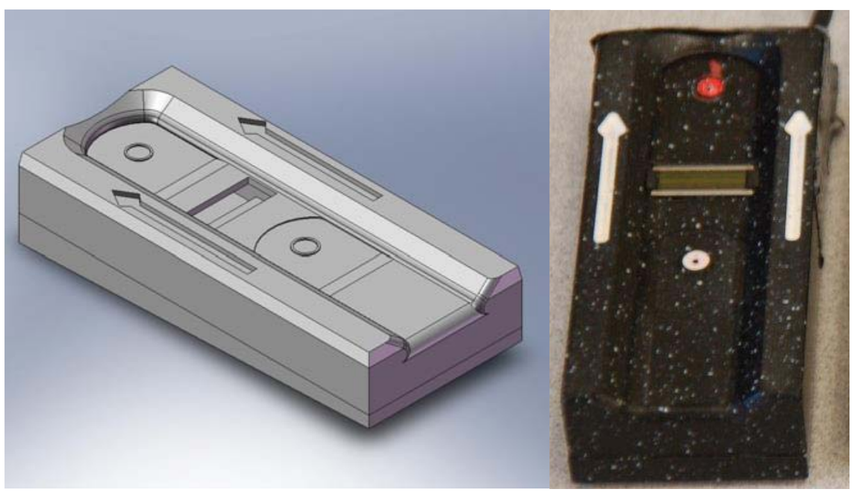


Figure 81 Final CAD model (left) and image (right) of the push form factor.

4.2.3. Manufacturing Process

Upon completion of the three-dimensional solid modeling of the form factor devices, CNC code was created for the push and pull models, and the parts were manufactured.

The manufacturing process brought about modifications that were unplanned between the modeling and manufacturing phases. First, the planned material for the form factor devices was a plastic composite material, similar to the commercial sensors used in this study. However, during machining a difference in the plastic composite material was evident, as one plastic block was “harder” than the others available. The hard plastic composite material worked well during machining but was too thin, and the black plastic composite blocks melted during the machine processes because the material was too soft (Figure 82). Thus, alternative materials had to be considered.

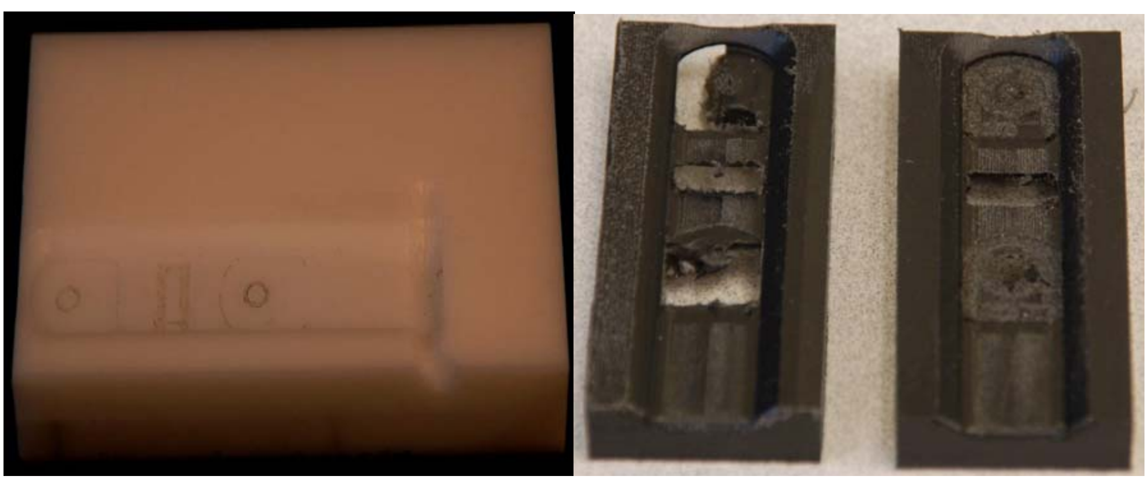


Figure 82 Plastic composite materials used for phase 1 machining. The white plastic composite was too thin (left) and the black plastic composite was too soft (right).

The next material of choice due to its smoothness and ability to be machined was the thermosetting plastic composed of acrylic polymer and alumina trihydrate, commonly known as Corian®. Slight modifications to the design had to be made due to the hardness of the material. First, the sensor had to be repositioned in the vice of the mill due to the material “flexing”, causing a widening of the finger channel (Figure 83 left). Modifications to sensor dimensions were also made due to material breakage (Figure 83 middle). Additionally, a relief point for the sensor circuit board had to be decreased due to the tooling breaking through the material towards the back end of the form factor (Figure 83 right). Third, and the most noticeable change in the design of the push and pull form factor was in the bottom half of the device.

Figure 83 Phase 2 fabricated form factors using Corian® requiring adjustments to the positioning in the mill (left and middle) and in the CNC code (right).

The original design of the pull form factor (Figure 78 middle) was to have a 3-5 degree incline from front to back and the push form factor (Figure 80 middle) was to have a 3-5 degree decline from back to front, which is similar to the commercial swipe fingerprint devices (Figure 55). However, the tolerance of the mill and tools could not handle such a tool path. Thus, the final bottom halves to the form factor designs were modified to be flat. The final fabricated form factor components are shown in Figure 84. Appendix S contains the two-dimensional engineering drawings for both the PUSH and PULL form factors, as well as images of the manufacturing process for the top half of the push and pull form factor.

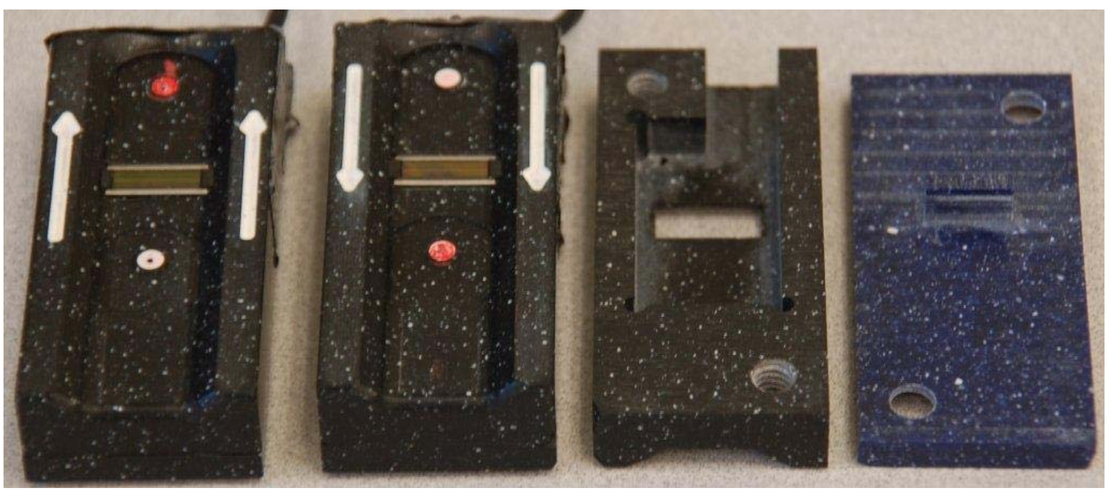


Figure 84 Final form factor components. From left to right: push top, pull top, reverse side of the top of both form factors, and the bottom half used for both form factors.

4.3. Phase 3: Quantitative Data

The quantitative component of this study consisted of collecting fingerprint images from 85 individuals on three swipe-based sensors and one large area sensor over three visits. The purpose of the quantitative portion of this study was to evaluate one commercial swipe-based fingerprint sensor, the two swipe-based fingerprint sensors created in section 4.2, and one commercial large area fingerprint sensor in a comparative performance evaluation using the HBSI evaluation method. The quantitative data and analysis section consists of four parts: volunteer crew, ergonomics and image quality, usability, and biometric performance.

4.3.1. Volunteer Crew in Phase 3

4.3.1.1. Demographics

The volunteer crew that participated in the quantitative study consisted of 85 individuals. The dropout rate was 2.29%, where the failure to show up for the first appointment was 17.48%, or 18 individuals of 103. Of the 85, 48 were female, 59 were under the age of 30, 59 classified their ethnicity as white, and 71 of the test participants self-reported their right hand as dominant (Figure 85).

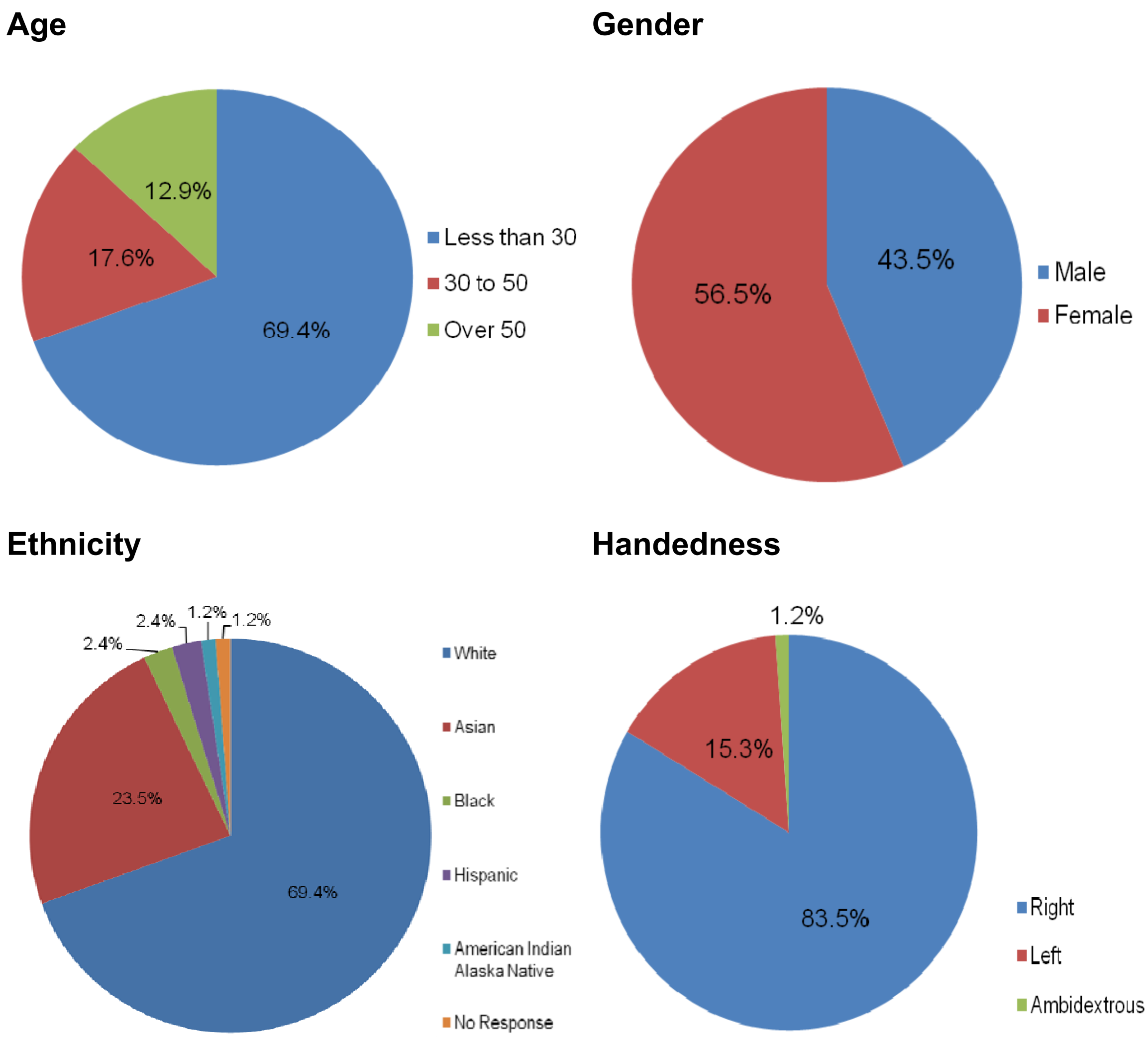


Figure 85 Participant age, gender, ethnicity, and handedness demographic information.

To further understand the volunteer crew, the US Department of Labor Standard Occupational Classification (SOC) user guide (2004), which classifies occupations into 23 major groups, was referenced. The 23 groups were condensed into eight groups, with one added to include students who do not work. The nine occupation groups used were:

- Administrative, business, legal, education, sales, and computer;

- Healthcare practitioners and technician;
- Agriculture;
- Construction, installation, maintenance, production, and transportation;
- Art and design;
- Food preparation and service;
- Engineering, life, or physical sciences;
- Military and protective services; and
- Full or part time student and do not work.

Over 80% of the participants were either full time or part time students who did not work or workers in administrative, business, educators, or computer related fields (Figure 86). The other category of Figure 86 includes one individual in each of the following categories: volunteer, military and protective services, art and design, healthcare practitioners and technician, and agriculture.

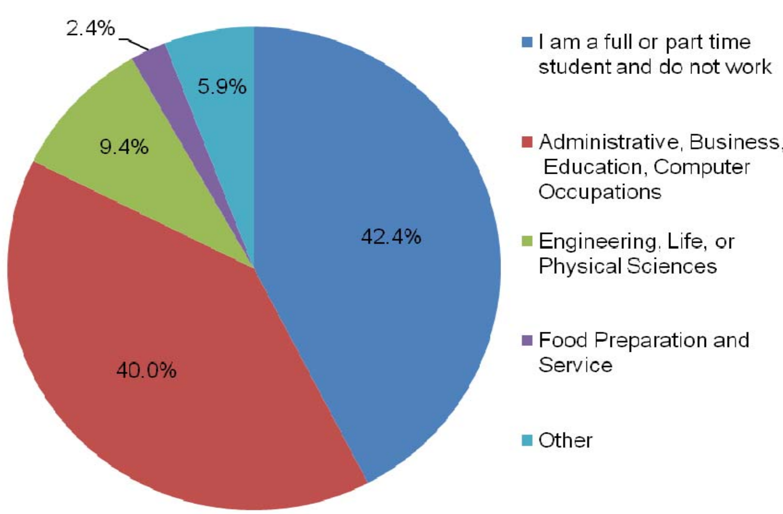


Figure 86 Self-reported occupation classification of the volunteer crew.

4.3.1.2. Prior use of fingerprint recognition

Prior usage of fingerprint recognition was self-reported to further understand participants and previous experience with the fingerprint sensors under study. Overall, 91.8% (78) of the participants reported using some form of fingerprint recognition prior to this study. From the 78 participants who had used fingerprint sensors prior to this study, over 25% of the participants self-reported having only used one sensor technology (Figure 87), 15% reported using two technologies (Figure 88), and almost 59% reported using three fingerprint recognition technologies (Figure 89). During the time of data collection, another fingerprint study involving a thermal sensor was used. Only one individual identified the thermal sensor, which is shown in Figure 89.

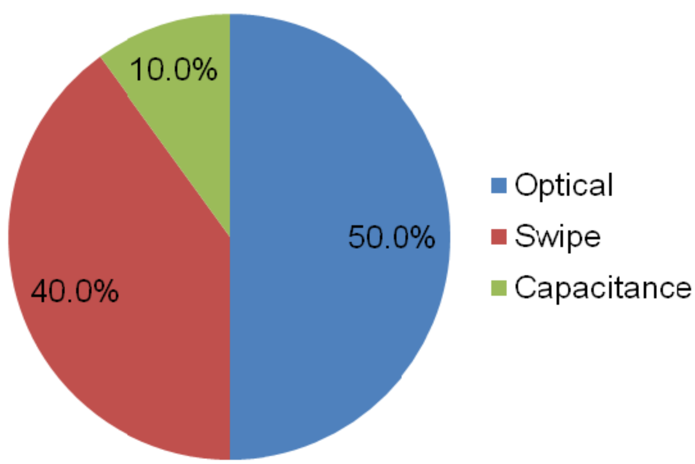


Figure 87 Prior fingerprint usage for one sensor technology.

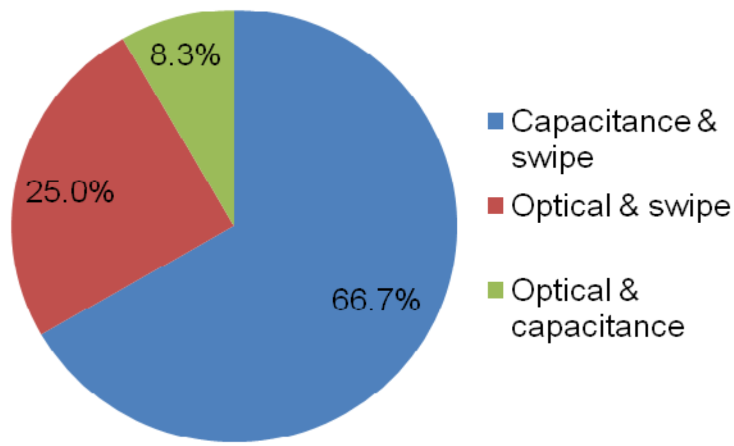


Figure 88 Prior fingerprint usage for two sensor technologies.

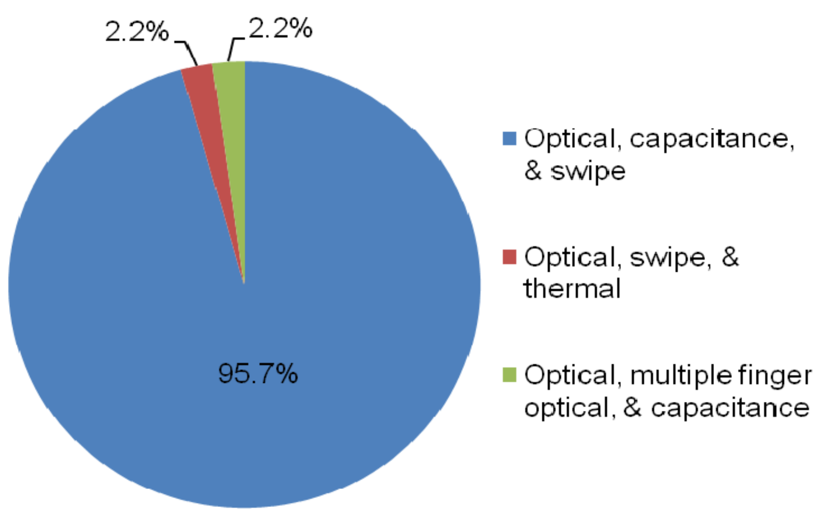


Figure 89 Prior fingerprint usage for three sensor technologies.

4.3.1.3. Anthropometric measurements

Anthropometric measurements were recorded for each participant in order to better understand the human variability of the volunteer crew used in this study. The following anthropometric measurements were collected:

- Hand length (LH and RH length);
- Hand breadth (LH and RH breadth);

- Length of Index finger (LI and RI length);
- Breadth of Index proximal interphalangeal joint (LI and RI PIPJ);
- Breadth of Index distal interphalangeal joint (LI and RI DIPJ); and
- Circumference of Index distal interphalangeal joint (DIPJ).

The descriptive statistics for the anthropometric measurements are reported by male (Table 30) and female (Table 31). The percentiles listed in the tables were used to create the categorical variables of small, medium, and large for the anthropometric measurements used later in the analysis.

Table 30 Anthropometric measurements for the males in the study.

Variable	N	Mean	Median	StDev	Min	33rd %ile	67th %ile	Max
LI DIPJ	37	17.93	18.28	1.12	15.85	17.26	18.60	19.97
RI DIPJ	37	17.74	17.70	1.32	14.80	17.08	18.47	19.80
LH breadth	37	90.77	90.84	4.43	81.62	88.94	92.58	99.83
RH breadth	37	90.38	90.61	4.10	80.00	88.66	92.12	99.88
LH length	37	192.22	193.40	8.20	172.00	189.62	196.76	207.94
RH length	37	192.07	192.67	7.92	174.22	190.34	194.68	212.47
LI length	37	77.08	77.86	4.31	67.52	75.15	79.12	89.75
RI length	37	76.91	77.62	4.13	67.23	75.65	78.72	88.95
LI PIPJ	37	20.29	20.20	1.17	18.12	19.75	20.86	22.70
RI PIPJ	37	20.37	20.60	1.54	17.11	19.60	20.84	23.50
LI Circum	37	4.79	4.90	0.30	4.10	4.69	5.00	5.20
RI Circum	37	4.94	5.00	0.27	4.30	4.89	5.10	5.50

Table 31 Anthropometric measurements for the females in the study.

Variable	N	Mean	Median	StDev	Min	33rd %ile	67th %ile	Max
LI DIPJ	48	16.28	16.26	1.08	14.44	15.58	16.88	18.69
RI DIPJ	48	16.29	16.34	1.42	12.93	15.70	17.01	18.75
LH breadth	48	81.68	81.87	4.23	71.74	80.21	83.64	92.16
RH breadth	48	81.61	81.60	4.58	72.03	79.53	83.42	89.62
LH length	48	175.75	175.22	7.22	157.08	172.81	177.71	189.53
RH length	48	175.49	175.39	8.30	153.88	172.38	178.97	192.88
LI length	48	70.98	70.78	4.01	60.43	69.64	72.86	80.48
RI length	48	71.06	71.05	4.26	59.19	69.06	72.63	80.76
LI PIPJ	48	18.34	18.16	1.29	16.46	17.62	18.85	22.57
RI PIPJ	48	18.53	18.40	1.56	14.88	17.79	19.34	21.85
LI Circum	48	4.29	4.30	0.29	3.80	4.10	4.40	4.90
RI Circum	48	4.50	4.50	0.29	3.80	4.30	4.60	5.20

4.3.2. Data Analysis Methodology

Section 3.3.8 outlines the data collection methodology and experimental design that were used in this study. Table 32 shows the how the five data collection components (DCC) were spaced over the three visits.

Table 32 Data collection methodology.

	Week			
	1	2	3	4
Data Collection Component (DCC)	Visit 1 Training Enrollment Matching 1	Visit 2 Matching 2		Visit 3 Matching 3

Visit one consisted of training, enrollment, and matching 1. Since all the data were analyzed offline, the terms enrollment and matching do not refer to the actual process of the biometric sub-system enrolling or matching at the time of capture, rather served as instructions regarding the task that participants were to complete. Visit two consisted of matching 2 and visit three consisted of matching 3. Each of the following sections of this chapter will report the results by the five data collection components according to the metrics contained in the HBSI evaluation method (Figure 90).

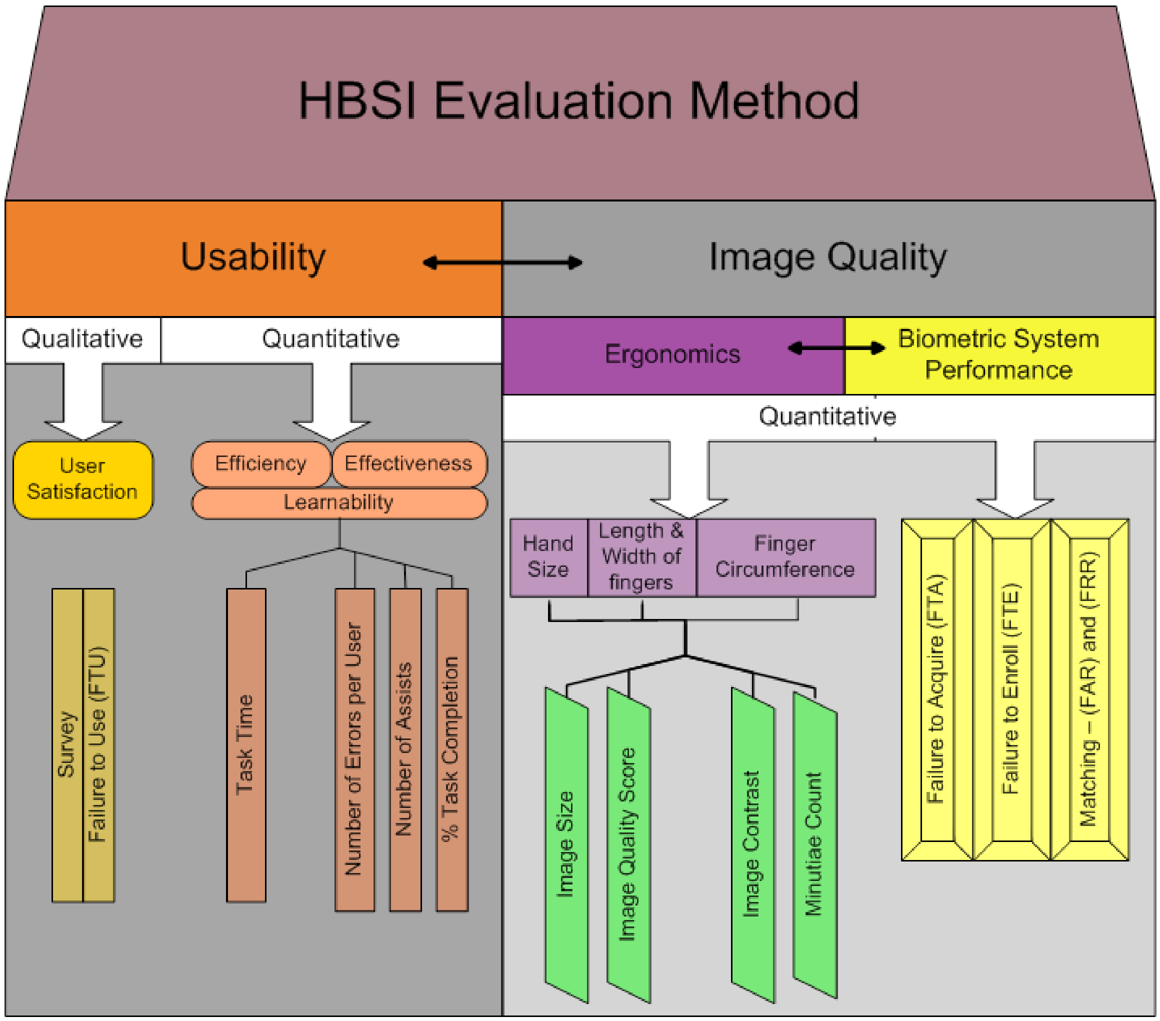


Figure 90 The HBSI evaluation method (Kukula, 2007; Kukula, Elliott, & Duffy, 2007).

The first area that will be discussed is image quality and ergonomics, which contain the following measurements: image quality, number of detected minutiae, fingerprint image area, and fingerprint image contrast. Three swipe-based sensors: UPEK, PUSH, and PULL will be used in this analysis. While data were collected on the large area (LA) sensor as well, these data were not included in the statistical tests, as the hypotheses were developed to test for statistical differences in the swipe-based sensors. However, the large area results are included in the descriptive statistics for information and comparison. Next, usability will be discussed. The HBSI usability questionnaire analysis included the three swipe-based sensors, whereas the remaining measures of usability: efficiency, learnability, and effectiveness analyzed all four sensors comparatively. Lastly, biometric system performance will be discussed and will compare all four sensors.

4.3.3. Image quality and ergonomics

The first metric of the HBSI evaluation method that will be discussed is image quality. As discussed in section 2.8.4.2.1.2, image quality consists of two components: ergonomics and biometric system performance. Results in this section are reported by each of the 5 data collection components: training, enrollment, visit 1 matching, visit 2 matching, and visit 3 matching. Results from the following ergonomic data analysis sections are reported: Aware and NFIQ image quality, number of detected minutiae, fingerprint image size, and fingerprint image contrast, or variation in the gray levels.

4.3.3.1. Aware and NFIQ Image Quality Analysis

Aware's Wavelet Scalar Quantization (WSQ) VBQuality software v2.42E was used to measure image quality as a continuous variable (0-99). The software reported the number of detected minutiae, shown in Figure 91. The detection of minutiae will be discussed in section 4.3.3.2. Figure 92 shows fingerprint images for five different image quality scores that were in the dataset.

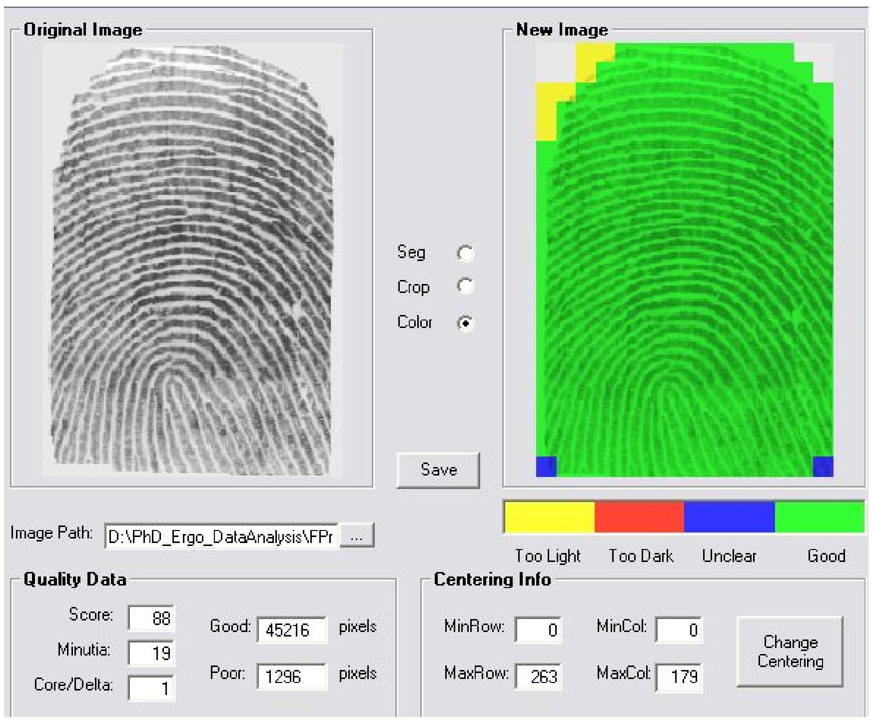


Figure 91 Aware's WSQ image quality software with an AIMQ score of 88 and 19 detected minutiae.

Figure 92 Fingerprint images with the Aware IMQ score reported below.

An alternate to the continuous image quality algorithm by Aware, is NFIQ, an image quality algorithm that is part of the NIST Biometric Image Software (NBIS) package. The NIST NFIQ algorithm reports quality scores on a nominal scale from one to five, with one being best quality and five an image of lowest quality. Figure 93 shows fingerprint images collected in this study at each NFIQ rank. For more information on the tools used to evaluate image quality, please refer to section 2.8.4.2.1.2.

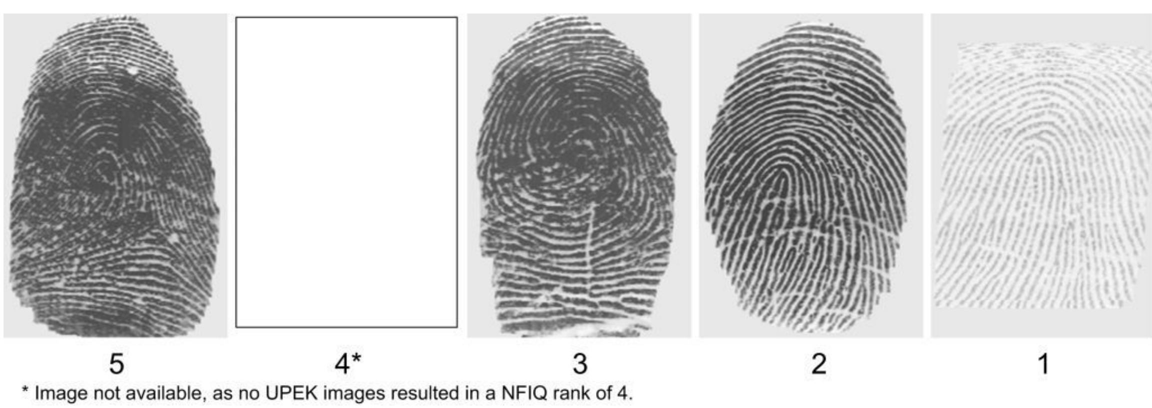


Figure 93 Fingerprint images and resultant NFIQ ranking.

The next five sections discuss the data and analysis involving fingerprint image quality. For the purpose of the statistical analyses and comparisons across the 3 swipe-based sensors, only the Aware Image Quality (AIMQ) algorithm was used. Note, the descriptive statistics for NFIQ are reported alongside AIMQ, but statistical analyses were not.

4.3.3.1.1. Aware Image Quality (AIMQ) Score Analysis

The hypothesis for image quality was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the Aware Image Quality (AIMQ) score of a swipe-based fingerprint image collected in each data collection component for all hand and finger sizes compared to the commercial UPEK sensor.

First, the assumptions of the Analysis of Variance (ANOVA) test with AIMQ were investigated. To test the assumptions of ANOVA, three model adequacy checks were conducted on the data to ensure the data was independent, normally distributed, and had equal variance.

Previous research involving fingerprint image quality using the Aware image quality algorithm had shown results to be skewed and non-normal due to the heavy tails of images with excellent and poor quality (Kukula, Elliott, Kim, & San Martin, 2007; Modi & Elliott, 2006b). The AIMQ data in this study exhibited similar behaviors. Figure 94 shows the adequacy check for AIMQ matching 1, which the normality plot (upper left) shows the data is not normally distributed.

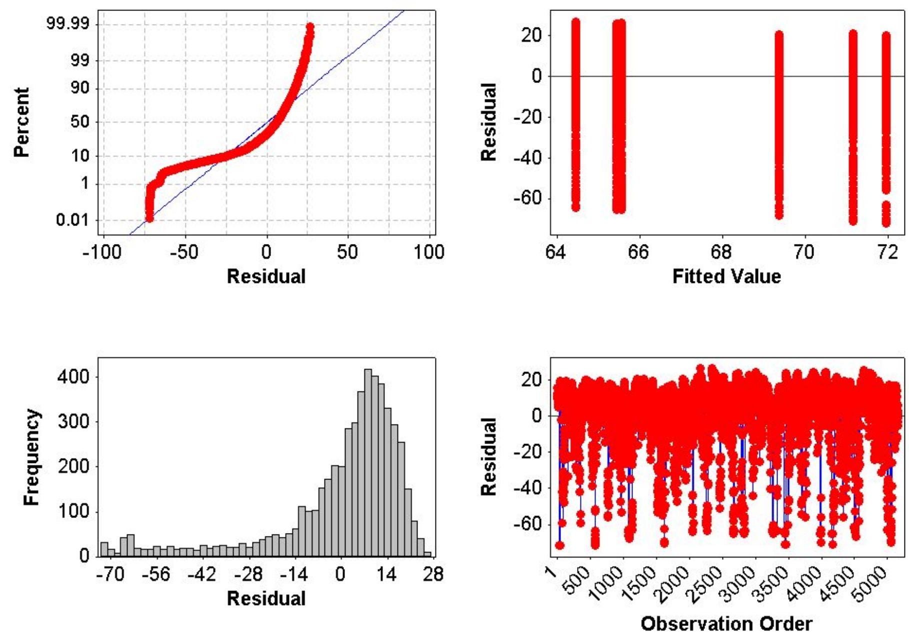


Figure 94 Example adequacy check of ANOVA model assumptions for AIMQ matching 1.

All five ANOVA adequacy checks for AIMQ can be found in Appendix T, which show the AIMQ data is not normally distributed for each DCC. However, according to Schuckers (2008) "it is not necessary to assume normality if you are doing a test of equal means (ANOVA) and you have large sample sizes per each level that you are testing. The *p* values should be appropriate." In the case of AIMQ, and all the following measures in this section, the sample sizes for training ($N \geq 600$), and enrollment, matching 1, 2, and 3 ($N \geq 1,600$) should be adequate for the Central Limit Theorem to hold. The second test that was conducted on the data was the Tukey pairwise comparison test, which was done to determine what sensor pairs were statistically different. Lastly, the descriptive statistics are included for each test to provide additional insight for the data under test, as well as compare to the baseline large area sensor.

4.3.3.1.1.1. AIMQ Results for Training

The hypothesis for AIMQ score for training was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the AIMQ score for the training images for all hand and finger sizes compared to the UPEK sensor.

First, a visual inspection of the AIMQ scores was conducted in the form of a histogram (Figure 95). The individual histograms segmented by swipe sensor show the distribution and spread of the data for training. The histograms show that the data are skewed to the left, with the UPEK having a more concentrated distribution than the PUSH or PULL, indicating UPEK may have produced images of higher quality. To further examine if a statistically significant difference was present, an ANOVA test was conducted.

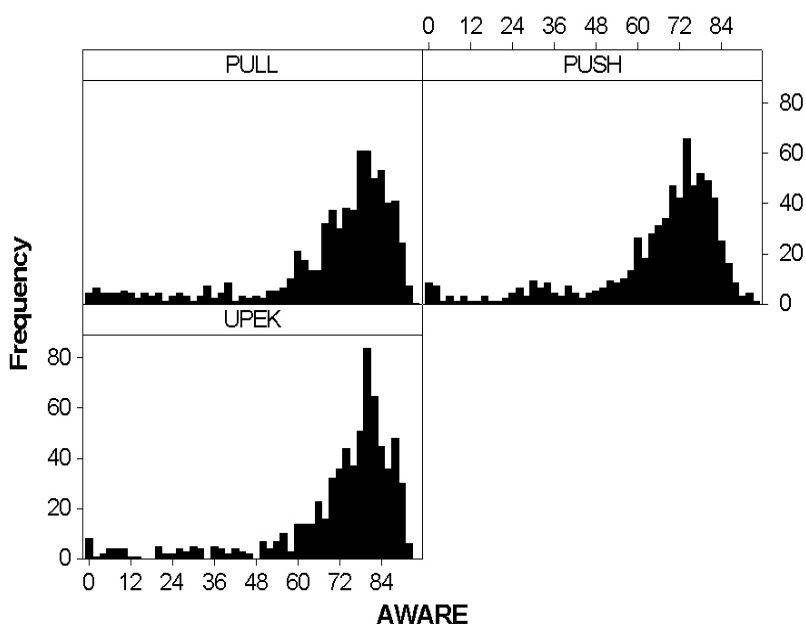


Figure 95 Histogram of training AIMQ scores.

As discussed in section 4.3.3.1.1 and shown in Appendix T, the ANOVA assumptions held. A two-factor ANOVA was performed at α of 0.05 with response AIMQ score and two factors: finger used and swipe sensor type. The results showed a significant main effect of finger used, $F(1,2064) = 14.41$, $p = 0.000$, with the right index (RI) fingerprint images producing a higher mean quality score than the left index (LI) images. The main effect of swipe sensor was also significant $F(2,2064) = 14.30$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,2064) = 0.32$, $p = 0.727$. Results of the Tukey pairwise comparison test are presented in Table 33 and reveal statistically significant differences in AIMQ scores for the UPEK and PUSH, and PUSH and PULL, but reveal no difference in AIMQ scores of the UPEK and PULL sensors. AIMQ descriptive statistics are shown in Table 34 to provide additional insight on the training data.

Concluding the analysis of AIMQ scores for training, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK.

Table 33 Training Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0016$	-
UPEK	$p = 0.1681$	$p = 0.000$

Table 34 IMQ score descriptive statistics for training by sensor.

		Mean		Median		StDev		Minimum		Maximum	
Sensor	N	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ
UPEK	696	70.97	2.57	77	2	19.03	1.07	0	5	91	1
PUSH	682	65.42	2.82	71	3	19.07	1.01	0	5	93	1
PULL	692	69.09	2.63	76	2	20.70	1.06	0	5	92	1
LA	694	51.99	2.57	53	2	16.12	1.08	4	5	85	1

4.3.3.1.1.2. AIMQ Results for Enrollment

The hypothesis for AIMQ scores for enrollment was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the AIMQ score for the enrollment images for all hand and finger sizes compared to the UPEK sensor.

First, a visual inspection of the AIMQ scores was conducted in the form of a histogram (Figure 96). The individual histograms by swipe sensor show the distribution and spread of the data for enrollment, which show that the data is skewed to the left, with the UPEK and PULL having a more concentrated distribution than the PUSH, indicating PUSH image quality is more variable. To further examine if a statistically significant difference was present, an ANOVA test was conducted.

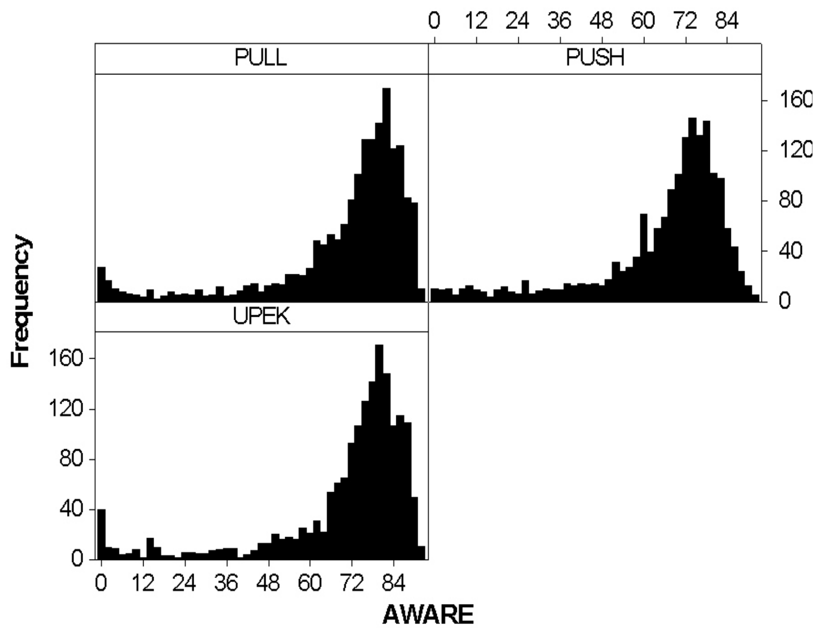


Figure 96 Histogram of enrollment AIMQ scores.

As discussed in section 4.3.3.1.1 and shown in Appendix T, the ANOVA assumptions held. A two-factor ANOVA was performed at α of 0.05 with response AIMQ score and two factors: finger used and swipe sensor type. The results showed a significant main effect of finger used, $F(1,5164) = 29.23$, $p = 0.000$, with fingerprint images from the RI producing a higher mean quality score than the LI. The main effect of swipe sensor was also significant $F(2,5164) = 28.83$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,5164) = 0.29$, $p = 0.751$. Results of the Tukey pairwise comparison test are presented in Table 35 and reveal statistically significant differences in AIMQ scores for the UPEK and PUSH, PUSH and PULL, but reveal no difference in AIMQ scores of the UPEK and PULL sensors. AIMQ descriptive statistics are shown in Table 36 to provide additional insight on the enrollment data.

Concluding the analysis of AIMQ scores for enrollment, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical difference was found between the PULL and UPEK.

Table 35 Enrollment Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0000	-
UPEK	p = 0.8684	p = 0.000

Table 36 IMQ score descriptive statistics for enrollment by sensor.

		Mean		Median		StDev		Minimum		Maximum	
Sensor	N	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ
UPEK	1735	69.46	2.62	76	2	20.82	1.10	0	5	91	1
PUSH	1695	65.14	2.84	71	3	19.11	1.00	0	5	92	1
PULL	1740	69.80	2.67	76	2	20.28	1.14	0	5	92	1
LA	1740	52.85	1.89	55	2	16.48	0.98	7	5	84	1

4.3.3.1.1.3. AIMQ Results for Matching Visit 1

The hypothesis for AIMQ scores for matching visit 1 was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the AIMQ score for the matching visit 1 images for all hand and finger sizes compared to the UPEK sensor.

First, a visual inspection of the AIMQ scores was conducted in the form of a histogram (Figure 97). The individual histograms by swipe sensor show the distribution and spread of the data for matching images collected in visit 1. The histograms show that the data are skewed to the left, with the UPEK having a more concentrated distribution than the PULL and PUSH sensors. The descriptive statistics (Table 37) provide additional data about the matching visit 1 AIMQ scores.

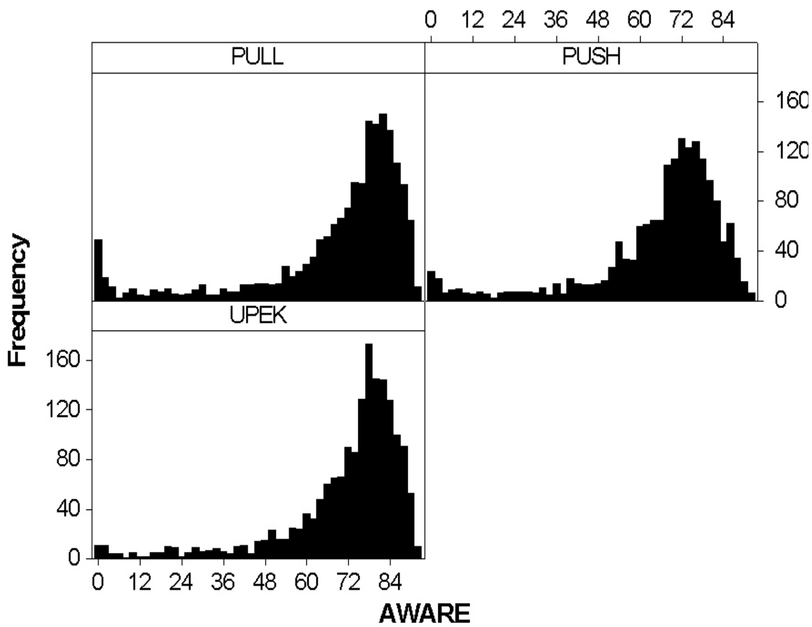


Figure 97 Histogram of matching visit 1 AIMQ scores.

Table 37 IMQ score descriptive statistics for matching visit 1 by sensor.

		Mean		Median		StDev		Minimum		Maximum	
Sensor	N	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ
UPEK	1730	70.65	2.64	76	2	17.76	1.12	0	5	92	1
PUSH	1687	65.01	2.82	70	3	19.33	0.98	0	5	92	1
PULL	1740	68.30	2.67	76	2	22.03	1.12	0	5	92	1
LA	1740	51.69	1.90	53	2	16.39	0.97	0	5	84	1

To further examine if a statistically significant difference was present, an ANOVA test was conducted. As discussed in section 4.3.3.1.1 and shown in Appendix T, the ANOVA assumptions held. A two-factor ANOVA was performed at α of 0.05 with response AIMQ score and two factors: finger used and swipe sensor type. The results showed a significant main effect of finger used, $F(1,5151) = 32.53$, $p = 0.000$, with fingerprint images from the RI producing a higher mean quality score than the LI. The main effect of swipe sensor was also significant $F(2,5151) = 35.42$, $p = 0.000$. There was a significant interaction between finger and sensor, $F(2,5151) = 6.13$, $p = 0.002$, which is shown in Figure 98. The interaction plot reveals that the RI AIMQ scores are of higher quality for all three swipe-based sensors, but the largest difference in means (5.3) for finger used and sensor type occurred with the PULL sensor. Interpreting the results of the plot for the matching visit 1 DCC, the UPEK sensor produced images of highest quality in terms of AIMQ and produced the most consistent quality images for both the RI and LI.

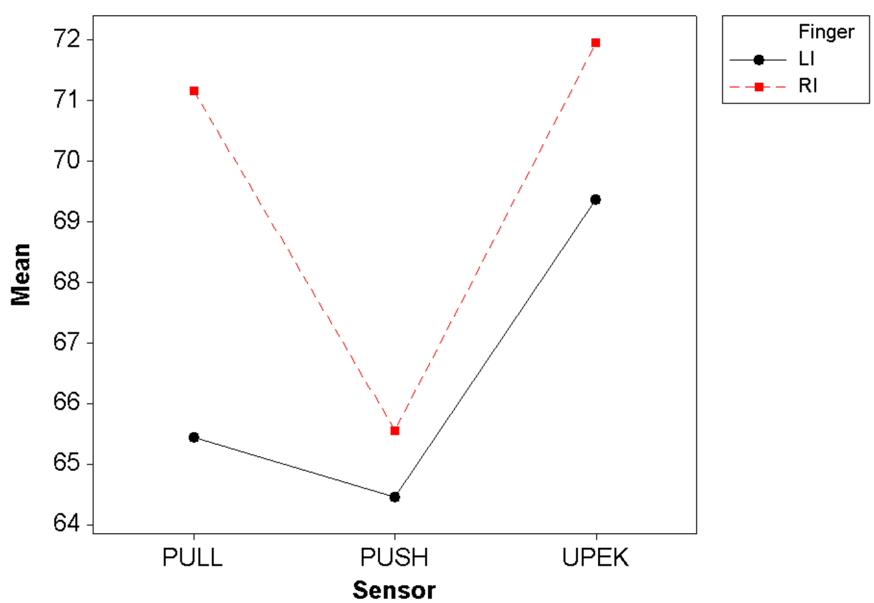


Figure 98 Finger*Sensor interaction plot of mean AIMQ scores for matching visit 1.

Results of the Tukey pairwise comparison test are presented in Table 38 and reveal statistically significant differences in AIMQ scores for all swipe sensor combinations. Examining all the data, it appears from the interaction plot that the UPEK sensor performed similarly in terms of AIMQ for both fingers, however large differences in the mean AIMQ score were seen between the right and left index fingers on the PULL sensor.

Table 38 Matching visit 1 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0000	-
UPEK	p = 0.0013	p = 0.0000

Concluding the analysis of AIMQ scores for matching visit 1, there was a significant difference between all three swipe sensor combinations.

4.3.3.1.1.4. AIMQ Results for Matching Visit 2

The hypothesis for AIMQ scores for matching visit 2 was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the AIMQ score for the matching visit 2 images for all hand and finger sizes compared to the UPEK sensor.

First, a visual inspection of the AIMQ scores was conducted in the form of a histogram (Figure 99). The individual histograms by swipe sensor show the distribution and spread of the data for matching images collected in visit 2. The histograms show that the data are skewed to the left, with the UPEK and PULL exhibiting a more concentrated distribution at the high quality end. The descriptive statistics (Table 39) provide additional data about the matching visit 2 AIMQ scores.

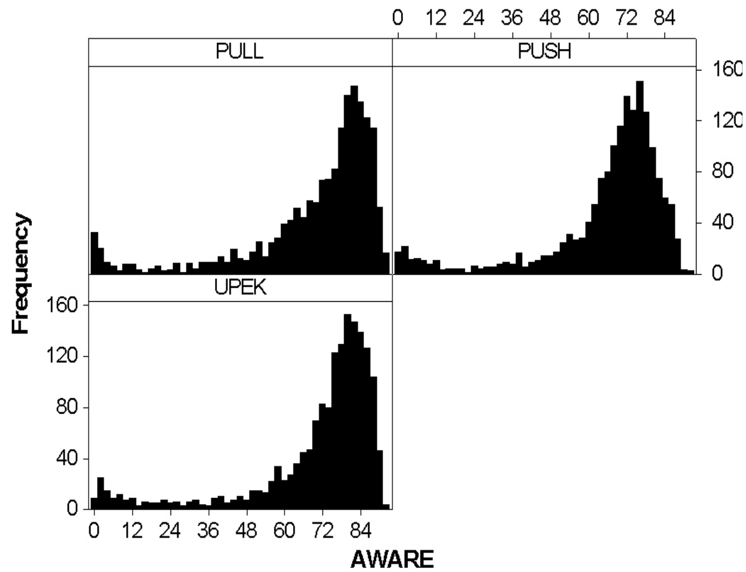


Figure 99 Histogram of matching visit 2 AIMQ scores.

Table 39 IMQ score descriptive statistics for matching visit 2 by sensor.

		Mean		Median		StDev		Minimum		Maximum	
Sensor	N	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ
UPEK	1677	69.72	2.56	77	2	20.69	1.08	0	5	91	1
PUSH	1670	65.32	2.82	71	3	19.29	0.98	0	5	91	1
PULL	1678	69.15	2.68	77	2	20.90	1.19	0	5	92	1
LA	1700	52.29	1.94	55	2	16.97	1.01	0	5	86	1

To further examine if a statistically significant difference was present, an ANOVA test was conducted. As discussed in section 4.3.3.1.1 and shown in Figure 128 of Appendix T, the ANOVA assumptions held. A two-factor ANOVA was performed at α of 0.05 with response AIMQ score and two factors: finger used and swipe sensor type. The results showed a significant main effect of finger used, $F(1,5019) = 36.68$, $p = 0.000$, with fingerprint images from the RI producing a higher mean quality score than the LI. The main effect of swipe sensor was also significant $F(2, 5019) = 23.47$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2, 5019) = 2.97$, $p = 0.051$, however as this is close to the significance level (α) of 0.05, the interaction plot is shown in Figure 100 to further investigate this analysis. The interaction plot reveals that the RI AIMQ scores are of higher quality for all three swipe-based sensors, but the largest difference in means for finger used and sensor type was again the PULL sensor, although the mean RI AIMQ was higher than the UPEK RI, which is an improvement over DCC matching visit 1. Interpreting the results of the plot for the matching visit 2 DCC, the UPEK sensor produced the most consistent quality images as it resulted in similar mean AIMQ scores for both the RI and LI.

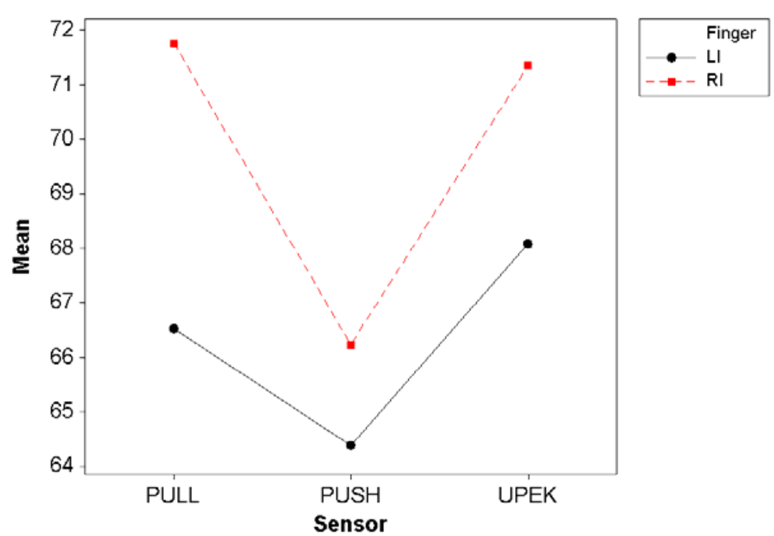


Figure 100 Finger*Sensor interaction plot of mean AIMQ scores for matching visit 2.

Results of the Tukey pairwise comparison test are presented in Table 40 and reveal statistically significant differences in AIMQ scores for the all swipe sensor combinations except for UPEK and PULL. Examining all the data, it appears from the interaction plot that the left index AIMQ average score was lower for left index finger images for all three swipe sensors. Furthermore, the right index finger average AIMQ score for the PULL sensor was of highest quality.

Table 40 Matching visit 2 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0000	-
UPEK	p = 0.6985	p = 0.0000

Concluding the analysis of AIMQ scores for matching visit 2, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK.

4.3.3.1.1.5. AIMQ Results for Matching Visit 3

The hypothesis for AIMQ matching visit 3 was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the AIMQ score for the images collected during matching visit 3 for all hand and finger sizes compared to the UPEK sensor.

Visual inspection of the AIMQ scores was conducted and is shown in Figure 101. The individual histograms by swipe sensor show the distribution and spread of the data for matching visit 3. The histograms show that the data are skewed to the left, with the UPEK having a more concentrated distribution than the PUSH or PULL, indicating UPEK may have produced images of higher quality. The descriptive statistics for the sensors used in the study can also be seen in Table 41.

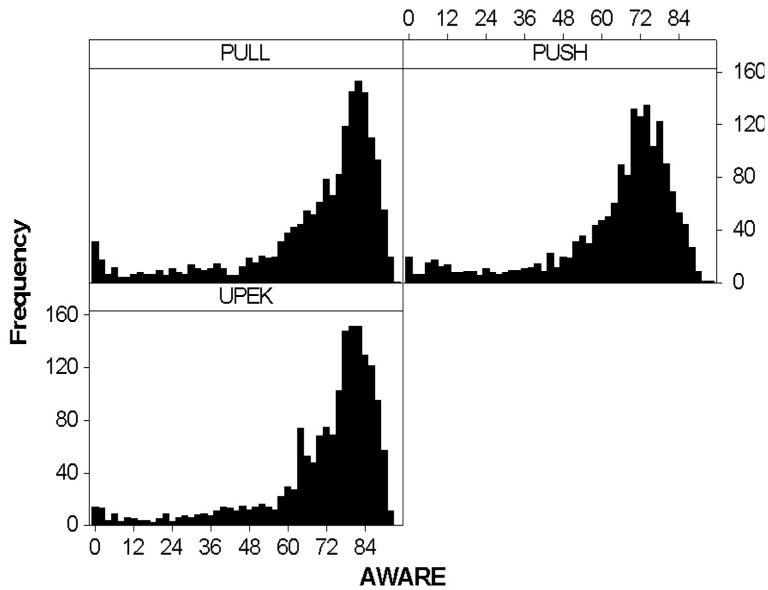


Figure 101 Histogram of matching visit 3 AIMQ scores.

Table 41 IMQ score descriptive statistics for matching visit 3 by sensor.

		Mean		Median		StDev		Minimum		Maximum	
Sensor	N	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ	Aware	NFIQ
UPEK	1691	70.31	2.63	77	2	19.10	1.09	0	5	92	1
PUSH	1659	63.53	2.89	70	3	20.04	0.99	0	5	93	1
PULL	1697	68.32	2.72	76	2	21.55	1.18	0	5	92	1
LA	1700	53.04	1.92	55	2	16.17	0.95	0	5	84	1

To further examine if a statistically significant difference was present, an ANOVA test was conducted. As discussed in section 4.3.3.1.1 and shown in Appendix T, the ANOVA assumptions held. A two-factor ANOVA was performed at α of 0.05 with response AIMQ score and two factors: finger used and swipe sensor type.

The results showed a significant main effect of finger used, $F(1,5041) = 69.76$, $p = 0.000$, with fingerprint images from the RI producing a higher mean quality score than the LI. The main effect of swipe sensor was also significant $F(2,5041) = 50.34$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,5041) = 2.70$, $p = 0.068$. Results of the Tukey pairwise comparison test are presented in Table 42 and reveal statistically significant differences in AIMQ scores for all sensor combinations.

Table 42 Matching visit 3 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0000$	-
UPEK	$p = 0.0102$	$p = 0.0000$

Concluding the analysis of AIMQ scores for matching visit 3, there was a significant difference between all three swipe sensor combinations.

4.3.3.1.2. Hypothesis Testing Summary: Image Quality

The hypothesis for image quality was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the AIMQ score of a swipe-based fingerprint images collected during training, enrollment, matching visit 1, 2, and 3 for all hand and finger sizes compared to the commercially available sensor.

Results for Aware image quality score statistical test revealed significant differences in both tested effects: finger and sensor type for all data collection components. The RI produced higher reported AIMQ scores than the LI for each data component tested. In addition, the interaction effect of finger*sensor was significant for matching visit 1 only, but was close to the significance value for all three matching modes. The interaction plots show that the RI fingerprint images had higher AIMQ mean scores and that there was a smaller difference in mean AIMQ for the PUSH and UPEK sensor than the PULL sensor. Tukey post hoc tests revealed pairwise differences among the mean AIMQ score for all the sensors in all five data collection components except for the PULL and UPEK during training, enrollment, and matching visit 2.

Investigating the UPEK and PULL swipe sensor AIMQ score mean, median, and standard deviation, the sensors appeared to capture fingerprints of similar quality compared to the PUSH sensor whose mean and median were continually lower than the UPEK and PULL, suggesting the design of the PUSH may assist in producing images of lower quality than the UPEK or PULL form factors. Table 43 summarizes the statistical testing for Aware image quality (AIMQ) scores.

Table 43 Summary of statistical testing for AIMQ.

	p-value			Post Hoc Analysis	Result
Data Collection Component (DCC)	Finger	Sensor	Finger*Sensor	Tukey Pairwise Comparison	Sensor Hypothesis Test (α = 0.05)
Training	0.0000	0.0000	0.7270	UPEK = PULL	Accept
Enrollment	0.0000	0.0000	0.7510	UPEK = PULL	Accept
Matching V1	0.0000	0.0000	0.0020	All pairwise differences significant	Accept
Matching V2	0.0000	0.0000	0.0510	UPEK = PULL	Accept
Matching V3	0.0000	0.0000	0.0680	All pairwise differences significant	Accept

4.3.3.2. Number of detected minutiae

The second metric of the HBSI evaluation method that will be discussed is number of detected minutiae. This measure varies according to how the human interacts with the sensor and where the finger is placed, amongst other factors. The hypothesis for the number of detected minutiae that was evaluated for both index fingers and each of the five data collection components: training, enrollment, matching 1, matching 2, and matching 3 was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the number of detected minutiae in a swipe-based fingerprint image collected in each data collection component for all hand and finger sizes compared to the commercial UPEK sensor.

To investigate the hypothesis for the number of detected minutiae in each data collection component, the same statistical process that as discussed in the image quality section above (4.3.3.1). The assumptions of the Analysis of Variance (ANOVA) test was investigated, with the results satisfying the assumptions of ANOVA, which are shown in Appendix U for each data collection component.

4.3.3.2.1. Results for the Number of Detected Minutiae for Training

The hypothesis for the number of detected minutiae for training was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the number of detected minutiae for the swipe fingerprint images collected during training for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the average minutiae count was different between the three swipe-based sensors and two fingers. The results showed a significant main effect of finger used, $F(1,2756) = 8.60$, $p = 0.003$, with fingerprint images from the LI detecting a higher mean number of minutiae than the RI. This difference could have been due to the experimental design. All participants started with their right index finger, and then used their left index finger. This will be of interest to observe over the remaining four data collection components, as the participants become more acclimated and habituated to the devices. The main effect of form factor type was significant $F(2,2064) = 29.47$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,2064) = 0.13$, $p = 0.876$. Results of the Tukey pairwise comparison test are presented in Table 44 and reveal there was no statistically significant difference in number of detected minutiae between the UPEK and PULL sensors, but there are across the UPEK/PUSH and PUSH/PULL. Table 45 provides the descriptive statistics for all the tested sensors to provide additional insight on the training data.

Table 44 Training Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0000$	-
UPEK	$p = 0.9967$	$p = 0.0000$

Table 45 Minutiae count descriptive statistics for training by sensor.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	696	32.685	33	9.953	1	66
PUSH	682	29.109	29	9.859	0	63
PULL	692	32.723	33	10.299	2	65
LA	694	44.939	44	10.54	11	94

Concluding the analysis for the number of detected minutiae for training, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK.

4.3.3.2.2. Results for the Number of Detected Minutiae for Enrollment

The hypothesis for the number of detected minutiae for enrollment was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the number of detected minutiae for the swipe fingerprint images collected during enrollment for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the average minutiae count was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results showed a significant main effect of finger used, $F(1,5164) = 19.24$, $p = 0.000$, with images from the LI having on average more minutiae than images from the RI. The main effect of form factor type was significant $F(2,5164) = 66.22$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,5164) = 0.36$, $p = 0.695$. Results of the Tukey test for pairwise comparisons are presented in Table 47 that reveal that there were no differences in the UPEK and PULL form factors, however there were across the UPEK-PUSH and PUSH-PULL sensors. To provide further insight regarding the minutiae data for enrollment, the descriptive statistics are listed in Table 47.

Table 46 Enrollment Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	*p* = 0.0000	-
UPEK	*p* = 0.5231	*p* = 0.0000

Table 47 Minutiae count enrollment descriptive statistics by sensor.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1735	32.189	33	10.785	0	67
PUSH	1695	28.932	29	9.488	0	65
PULL	1740	32.56	33	10.113	2	69
LA	1740	44.358	44	10.145	16	83

Concluding the analysis for the number of detected minutiae for enrollment, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK.

4.3.3.2.3. Results for the Number of Detected Minutiae for Matching 1

The hypothesis for the number of detected minutiae for images collected during visit 1 matching was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the number of detected minutiae for the swipe fingerprint images collected during matching 1 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the average minutiae count was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results showed a significant main effect of finger used, $F(1,5151) = 29.50$, $p = 0.000$. The main effect of form factor type was significant $F(2,5151) = 84.50$, $p = 0.000$. There was a significant interaction between finger and sensor, $F(2,5151) = 4.16$, $p = 0.016$, which is shown in Figure 102. Note that while the UPEK sensor detects more minutiae with the LI, the difference in means for the PULL RI and LI are negligible and are of similar values as the number of minutiae detected with the UPEK RI.

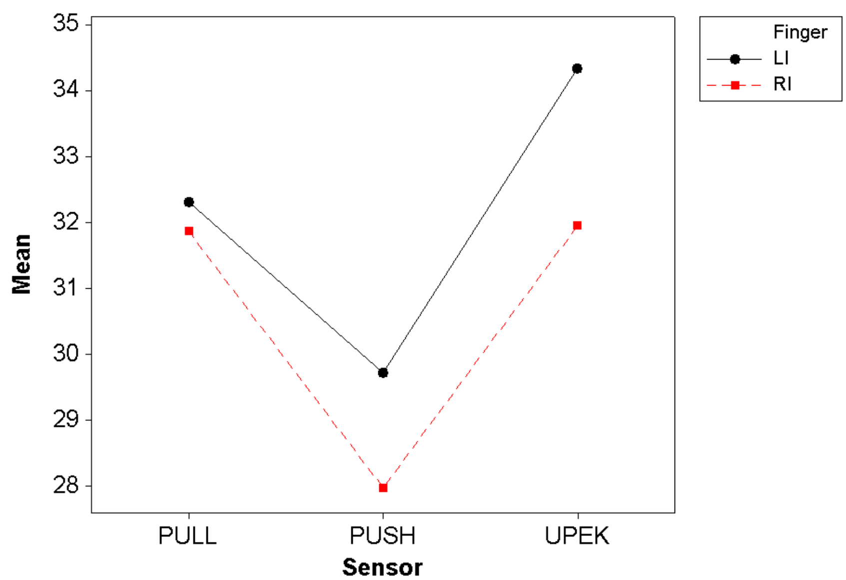


Figure 102 Finger*Sensor interaction plot of mean number of detected minutiae for matching visit 1.

Results of the Tukey test for pairwise comparisons are presented in Table 48 that reveal all sensor pairs were statistically different. To provide additional insight about the number of detected minutiae for matching 1 the descriptive statistics are listed in Table 49.

Table 48 Matching visit 1 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0058	-
UPEK	p = 0.0000	p = 0.0000

Table 49 Minutiae count matching visit 1 descriptive statistics by sensor.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1730	33.149	33	9.912	1	68
PUSH	1687	28.835	29	9.78	0	60
PULL	1740	32.088	33	10.592	0	70
LA	1740	44.036	43	10.176	13	93

Concluding the analysis for the number of detected minutiae for visit 1 matching, there was a significant difference between all pairwise comparisons.

4.3.3.2.4. Results for the Number of Detected Minutiae for Matching 2

The hypothesis for the number of detected minutiae for images collected during visit 2 matching was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the number of detected minutiae for the swipe fingerprint images collected during matching 2 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the average minutiae count was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results for matching visit 2 showed a significant main effect of finger used, $F(1,5019) = 8.96$, $p = 0.003$. The main effect of form factor type was significant $F(2,5019) = 76.17$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,5019) = 2.90$, $p = 0.055$, but as the p-value was close to the tested significance value ($\alpha = 0.05$) the interaction plot is shown in Figure 103. Note that the difference in means for the PULL RI and LI is negligible and are higher than the UPEK RI and LI. Also of interest is the difference in means between the RI and LI of the UPEK sensor.

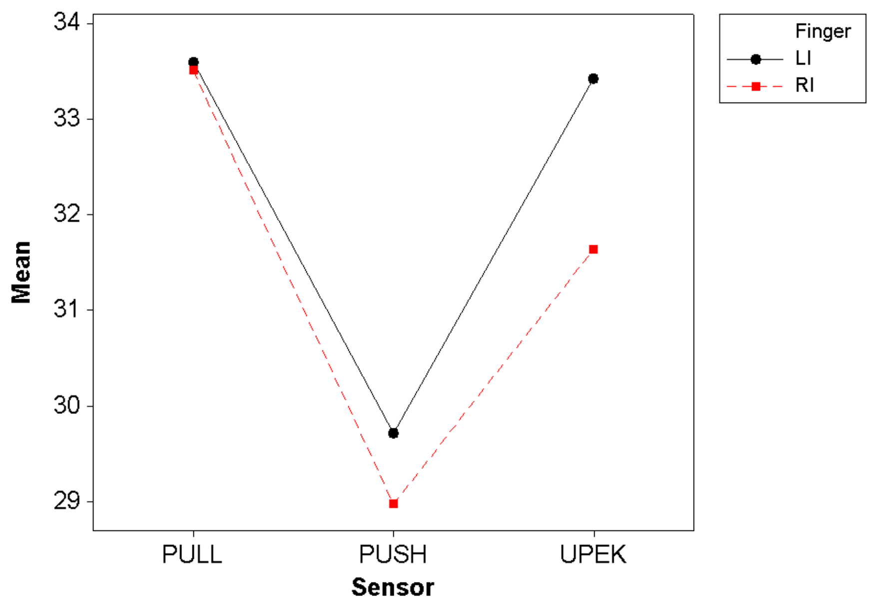


Figure 103 Finger*Sensor interaction plot of mean number of detected minutiae for matching visit 2.

Results of the Tukey test for pairwise comparisons are presented in Table 50 that reveals that all sensor pairs are different. Investigating the descriptive statistics (Table 51), the PULL sensor detected more minutiae on average than both the PUSH and PULL sensors.

Table 50 Matching visit 2 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0000	-
UPEK	p = 0.0114	p = 0.0000

Table 51 Minutiae count matching visit 2 descriptive statistics by sensor.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1677	32.534	33	10.143	1	71
PUSH	1670	29.341	29	9.853	1	67
PULL	1678	33.557	34	10.908	1	73
LA	1700	43.833	43	11.79	3	104

Concluding the analysis for the number of detected minutiae for visit 2 matching, there was a significant difference among all sensor pairs. Examining the descriptive statistics, the PULL sensor did detect more minutiae than the UPEK sensor, thus slight improvements to the detection of minutiae were realized. However, data from different populations are needed to determine the generalizability of this result.

4.3.3.2.5. Results for the Number of Detected Minutiae for Matching 3

The hypothesis for the number of detected minutiae for images collected during visit 3 matching was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the number of detected minutiae for the swipe fingerprint images collected during matching 3 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the average minutiae count was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results for matching visit 3 showed a significant main effect of finger used, $F(1,5041) = 2.75$, $p = 0.168$. The main effect of form factor type was significant $F(2,5041) = 644.98$, $p = 0.000$. There was a significant interaction between finger and sensor, $F(2,5041) = 3.17$, $p = 0.042$, which is shown in Figure 104. Note that the difference in means for the PULL RI and LI is negligible and are higher than the UPEK RI, but similar to the LI. Comparing the UPEK RI and LI for visit 2 matching (Figure 103), there is a reduction in the mean difference between the RI and LI, and that difference is larger than the difference between RI and LI for the PULL sensor.

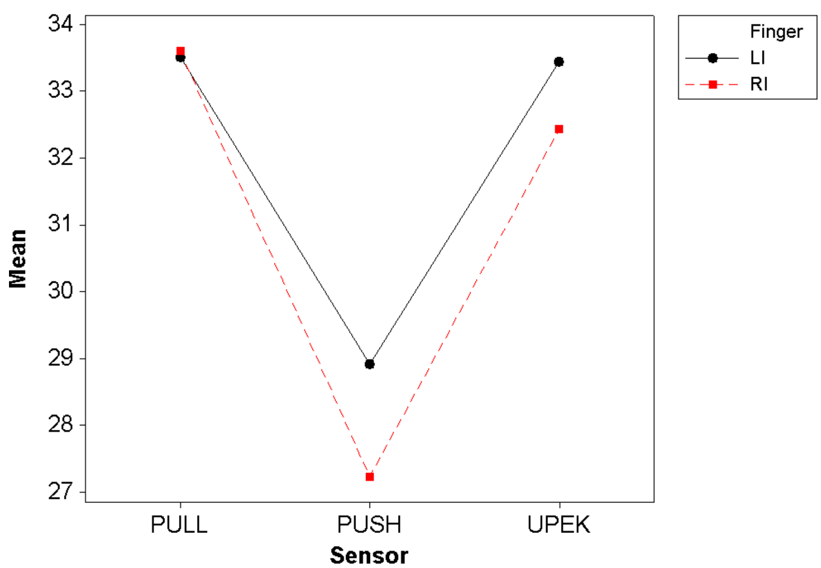


Figure 104 Finger*Sensor interaction plot of mean number of detected minutiae for matching visit 3.

Results of the Tukey test for pairwise comparisons are presented in Table 52, which reveal that there is no statistically significant difference in the mean number of minutiae detected with the UPEK and PULL sensors. There was a reported difference between the PUSH/UPEK and PUSH/PULL sensor pairs. Investigating the descriptive statistics (Table 53) the PULL sensor detected more minutiae on average than both the PUSH and UPEK sensors, but was not significantly different with the UPEK sensor.

Table 52 Matching visit 3 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0000$	-
UPEK	$p = 0.1861$	$p = 0.0000$

Table 53 Minutiae count matching visit 3 descriptive statistics by sensor.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1691	32.931	33	10.22	0	73
PUSH	1659	28.07	28	9.573	0	60
PULL	1697	33.549	34	11.09	2	70
LA	1700	43.47	43	10.813	7	106

Concluding the analysis for the number of detected minutiae for visit 2 matching, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK, although the PULL sensor did detect a higher mean number of minutiae and have a smaller difference in mean detected minutiae between the RI and LI than the UPEK sensor.

4.3.3.2.6. Hypothesis Testing Summary: Number of Detected Minutiae

The hypothesis for the number of detected minutiae tested for each of the 5 data collection component: training, enrollment, matching 1, 2, and 3 stated:

> The PUSH or PULL sensor will be significantly different in terms of the number of detected minutiae in a swipe-based fingerprint image collected in each data collection component for all hand and finger sizes compared to the commercial UPEK sensor.

Results for the number of detected minutiae statistical tests revealed statistical differences in both main effects: sensor type and finger used. The LI produced a larger mean number of detected minutiae than the RI for each data component tested. In addition, the interaction effect of finger*sensor was significant for matching visit 1 and 3 only. Tukey post hoc tests revealed differences in the mean number of detected minutiae for the PUSH/PULL and PUSH/UPEK sensor pairs in all five data collection components. However, the UPEK/PULL comparison revealed no statistical difference in the training, enrollment, or matching visit 3 data collection component.

Investigating the UPEK and PULL swipe sensor mean, median, and standard deviation, the sensors appeared to detect a similar number of minutiae compared to the PUSH sensor whose mean and median were continually lower than the UPEK and PULL, suggesting the design of the PUSH may result in detecting fewer minutiae points than the UPEK or PULL form factors. Table 54 summarizes the statistical testing for the number of detected minutiae.

Table 54 Summary of statistical testing for the number of detected minutiae.

	p-value			Post Hoc Analysis	Result
Data Collection Component (DCC)	Finger	Sensor	Finger*Sensor	Tukey Pairwise Comparison	Sensor Hypothesis Test (α = 0.05)
Training	0.003	0.000	0.876	UPEK = PULL	Accept
Enrollment	0.000	0.000	0.695	UPEK = PULL	Accept
Matching V1	0.000	0.000	0.016	All pairwise differences significant	Accept
Matching V2	0.003	0.000	0.055	All pairwise differences significant	Accept
Matching V3	0.003	0.000	0.042	UPEK = PULL	Accept

4.3.3.3. Matlab Tool for Fingerprint Image Size and Contrast

The next two measures of ergonomics and image quality are fingerprint image area and fingerprint image contrast. These were analyzed in Matlab v7.0.1. Dr. Young-Chul Song, a visiting post-doctoral scholar, developed the code in the BSPA Laboratory, which was called f4pro (Figure 105). For this research, the block size was set to 16x16. The purpose of the block size was to separate the fingerprint image into a background and fingerprint area regions.

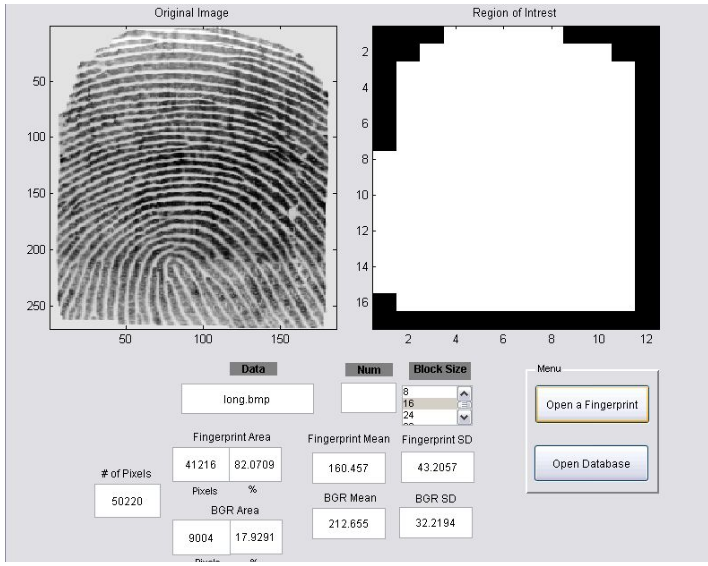


Figure 105 f4pro software for fingerprint image size and gray level contrast.

4.3.3.3.1. Fingerprint image size/area

The third metric of the HBSI evaluation method that is discussed is fingerprint image size. The fingerprint image size or area is defined as the portion of the image where details of the fingerprint ridges and valleys are. The measured size of the fingerprint images collected with the large area sensor and the three swiped-based sensors was expected to be significantly different, due to the differences in available pixels. The large area sensor has 92,160 available pixels whereas the swipe sensors have 50,220 available pixels (Figure 106). Therefore, like the other measures of image quality, only the three swipe-based sensors were compared during the statistical tests.

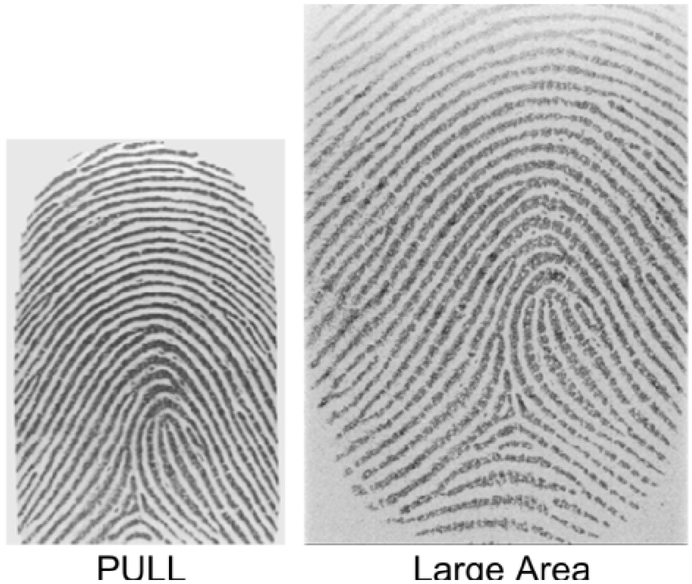


Figure 106 Example images from a swipe sensor and large area sensor used in this study showing the difference in available pixel sizes.

This measure is of importance to the HBSI as the area of the fingerprint image compared to the available pixels measures inconsistent contact and how users interact with fingerprint sensors. For example, if a sensor continuously captures fingerprint images that only fill 30-60% of the available pixels, users may have a difficult time interacting with a particular sensor. Likewise, if the variability of fingerprint image size is large across a particular population, it may negatively impact the ability of the algorithm to match fingerprints due to feature variability. To better illustrate the fingerprint image area, Figure 107 shows three fingerprint images from the UPEK sensor to illustrate three different image areas observed in this study.

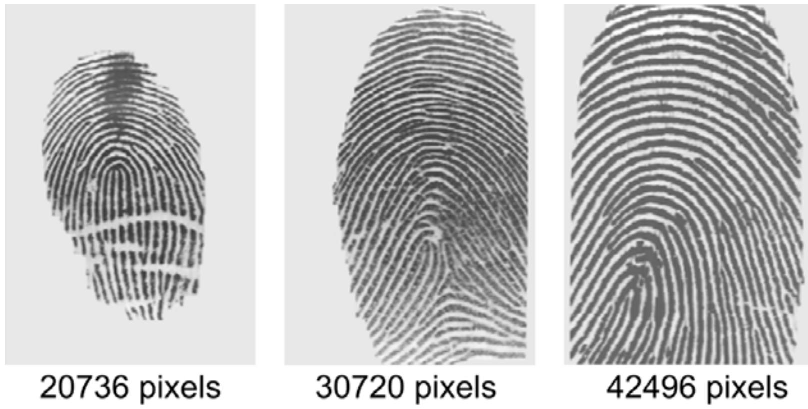


Figure 107 Example images from UPEK showing different image areas.

The hypothesis for the fingerprint image size that was evaluated for both index fingers and each of the five data collection components: training, enrollment, matching 1, matching 2, and matching 3 was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the size or area of the fingerprint in a swipe-based fingerprint image collected in each data collection component for all hand and finger sizes compared to the commercial UPEK sensor.

To investigate the hypothesis for the fingerprint image size in each data collection component, the statistical process that was discussed in the image quality and number of detected minutiae sections was followed. The assumptions of the Analysis of Variance (ANOVA) test were first investigated, with the results satisfying the assumptions of ANOVA, which are shown in Appendix V for each data collection component.

4.3.3.3.1.1. Fingerprint Image Size Results for Training

The hypothesis for fingerprint image size for the fingerprint images collected with the swipe sensors during training was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the size or area of the fingerprint for the swipe fingerprint images collected during training for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The results showed no main effect of finger used, $F(1,2064) = 0.90$, $p = 0.344$. The main effect of form factor type was significant $F(2,2064) = 195.71$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,2064) = 1.05$, $p = 0.349$. Results of the Tukey pairwise comparison test are presented in Table 55 and reveal there was no statistically significant difference in the image area of the fingerprints collected with the UPEK and PULL sensors, but there were across the remaining sensors.

Table 56 provides the descriptive statistics for all the tested sensors to provide additional insight on the training data.

Table 55 Training Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0000$	-
UPEK	$p = 0.6677$	$p = 0.0000$

Table 56 Fingerprint area descriptive statistics by sensor for training.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	696	35046	35840	3799	20736	42496
PUSH	682	31468	31744	4221	20992	41472
PULL	692	35228	36096	3882	22528	42496
LA	694	71116	71424	7982	38656	85504

Concluding the analysis for fingerprint image area for training, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK, although the PULL sensor had a larger mean and median fingerprint image size than the UPEK sensor. However, the descriptive statistics pertain only to the data collected and is not generalizable.

4.3.3.3.1.2. Fingerprint Image Size Results for Enrollment

The hypothesis for fingerprint image size for the fingerprint images collected with the swipe sensors during enrollment was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the size or area of the fingerprint for the swipe fingerprint images collected during enrollment for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The results showed no main effect of finger used, $F(1,5164) = 0.00$, $p = 0.991$. The main effect of form factor type was significant $F(2,5164) = 195.71$, $p = 0.000$. There was a significant interaction between finger and sensor,

$F(2,5164) = 7.88$, $p = 0.000$, which is shown in Figure 108. The interaction plot shows similar mean fingerprint image areas for both RI and LI for the UPEK and PULL sensors, but a significantly lower mean for the PUSH sensor. The behavior of the RI and LI for the PUSH sensor is interesting compared to the other sensors, but cannot be explained at this time. This would be interesting to investigate further.

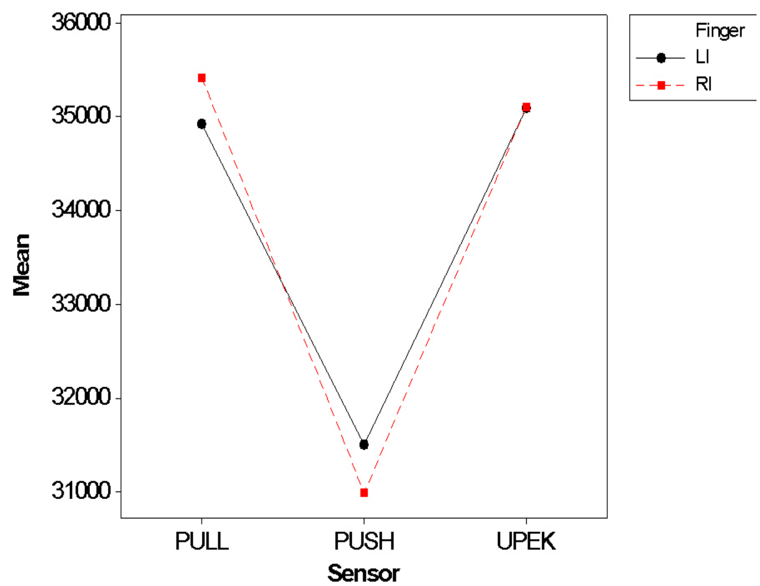


Figure 108 Finger*Sensor interaction plot of mean fingerprint image size for enrollment.

Results of the Tukey pairwise comparison test are presented in Table 57, which revealed that fingerprint image size was significantly different for each sensor type, except for those captured with the UPEK and PULL sensors. Table 58 provides the descriptive statistics for all the tested sensors to provide additional insight on the enrollment data.

Table 57 Enrollment Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	*p* = 0.0000	-
UPEK	*p* = 0.8352	*p* = 0.0000

Table 58 Fingerprint area descriptive statistics by sensor for enrollment.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1735	35098	35840	3455	21248	42752
PUSH	1695	31243	31232	3931	21504	40192
PULL	1740	35170	36096	3820	21504	41728
LA	1740	71097	71680	8030	35328	86272

Concluding the analysis for fingerprint image area for enrollment, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK, although the PULL sensor had a larger mean and median fingerprint image size than the UPEK sensor. However, like the training results the descriptive statistics for enrollment pertain only to the data collected and is not generalizable.

4.3.3.3.1.3. Fingerprint Image Size Results for Matching visit 1

The hypothesis for fingerprint image size for the fingerprint images collected with the swipe sensors during the matching visit 1 DCC was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the size or area of the fingerprint for the swipe fingerprint images collected during matching visit 1 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results showed no main effect of finger used, $F(1,5151) = 0.05$, $p = 0.830$. The main effect of form factor type was significant $F(2,5151) = 690.88$, $p = 0.000$. There was a significant interaction between finger and sensor, $F(2,5151) = 11.63$, $p = 0.000$, which is shown in Figure 109. The interaction plot shows similar mean fingerprint image areas for the PULL LI and UPEK RI and LI, but the PULL RI reported a larger mean image area. The PUSH sensor reported a significantly lower mean for both RI and LI. Like the enrollment data, the behavior of the interaction is interesting, but cannot be explained at this time.

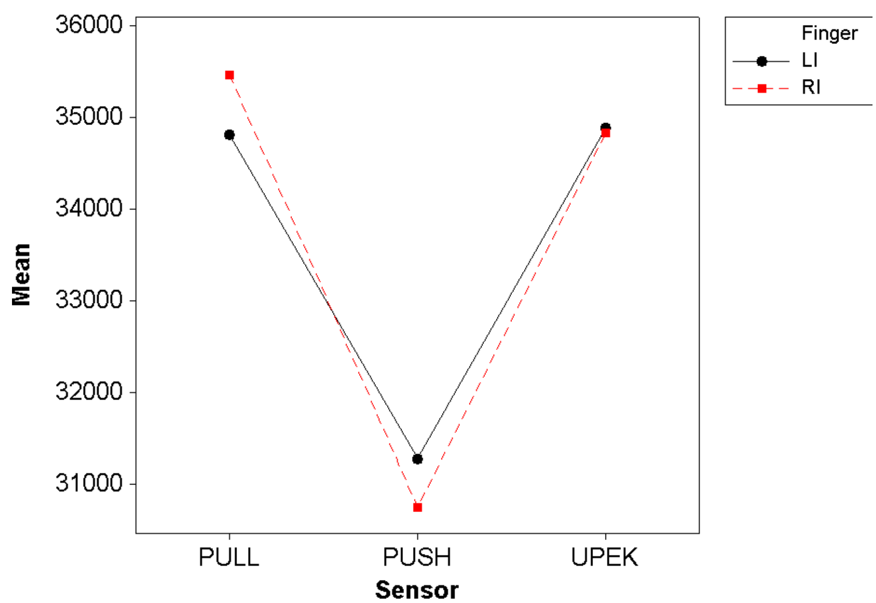


Figure 109 Finger*Sensor interaction plot of mean fingerprint image size for matching visit 1.

Results of the Tukey pairwise comparison test are presented in Table 59, which revealed that fingerprint image size was significantly different for each sensor type, except for those captured with the UPEK and PULL sensors. Note the reported *p*-value for the PULL-UPEK comparison is 0.0557, which was close to the significance level (α = 0.05). Table 60 provides the descriptive statistics for all the tested sensors to provide additional insight on the matching visit 1 data.

Table 59 Matching visit 1 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0000$	-
UPEK	$p = 0.0557$	$p = 0.0000$

Table 60 Fingerprint area descriptive statistics by sensor for matching visit 1.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1730	34854	35584	3533	21248	43520
PUSH	1687	31013	30464	3729	22016	39680
PULL	1740	35136	35840	3605	22016	41728
LA	1740	70114	70912	8083	41472	84992

Concluding the analysis for fingerprint image area for matching visit 1, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK, although the PULL sensor had a larger mean and median fingerprint image size than the UPEK sensor. However, the descriptive statistics pertain only to the data collected and is not generalizable.

4.3.3.3.1.4. Fingerprint Image Size Results for Matching visit 2

The hypothesis for fingerprint image size for the fingerprint images collected with the swipe sensors during the matching visit 2 DCC was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the size or area of the fingerprint for the swipe fingerprint images collected during matching visit 2 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results showed no main effect of finger used, $F(1,5019) = 1.91$, $p = 0.167$. The main effect of form factor type was significant $F(2,5019) = 632.93$, $p = 0.000$. There was a significant interaction between finger and sensor, $F(2,5019) = 6.07$, $p = 0.002$, which is shown in Figure 110. The interaction plot shows similar mean fingerprint image areas for the PULL RI and LI are both larger than the mean area for UPEK RI and LI. The PUSH sensor reported significantly lower mean fingerprint image areas for both RI and LI than the UPEK and PULL.

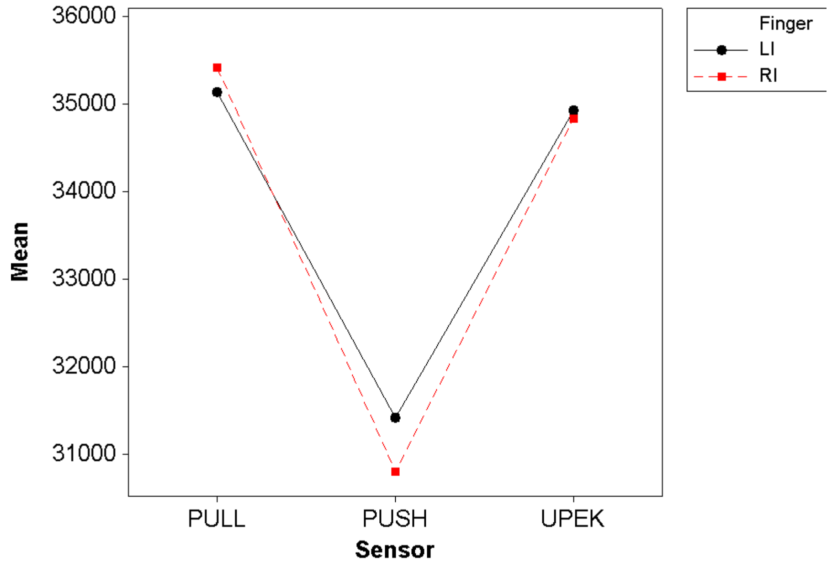


Figure 110 Finger*Sensor interaction plot of mean fingerprint image size for matching visit 2.

Results of the Tukey pairwise comparison test are presented in Table 61, which revealed that fingerprint image size was significantly different for each sensor comparison. Examining the interaction plot (Figure 110) and descriptive statistics (Table 62), we see that that the PULL sensor captured fingerprint images with the largest mean and median image size compared to the other two swipe-based sensors for the matching visit 2 DCC.

Table 61 Matching visit 2 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0000	-
UPEK	p = 0.0060	p = 0.0000

Table 62 Fingerprint area descriptive statistics by sensor for matching visit 2.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1677	34878	35584	3533	23296	41984
PUSH	1670	31110	30720	3910	20736	40960
PULL	1678	35274	36096	3762	22528	41984
LA	1700	70533	71424	8222	36864	87296

Concluding the analysis for fingerprint image area for matching visit 2, there was a significant difference between all sensor comparisons. In particular, the PULL sensor reported the largest improvement in mean image area from the DCCs thus far compared to the UPEK sensor. However these results are not generalizable and pertain to the population in this study only.

4.3.3.3.1.5. Fingerprint Image Size Results for Matching visit 3

The hypothesis for fingerprint image size for the fingerprint images collected with the swipe sensors during the matching visit 3 DCC was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the size or area of the fingerprint for the swipe fingerprint images collected during matching visit 3 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results showed no main effect of finger used, $F(1,5041) = 3.01$, $p = 0.083$. The main effect of form factor type was significant $F(2,5041) = 804.37$, $p = 0.000$. There was a significant interaction between finger and sensor, $F(2,5041) = 9.54$, $p = 0.000$, which is shown in Figure 111. The interaction plot shows similar mean fingerprint image areas for the PULL LI, and UPEK RI and LI. The PULL RI mean image area is the largest of all the swipe sensors for matching visit 3 DCC. Again, the PUSH sensor reported a significantly lower mean fingerprint image area for both RI and LI than the other two swipe-based sensors. It is interesting to note that in each interaction plot, the LI reported a larger mean image area than the RI for the PUSH in each DCC.

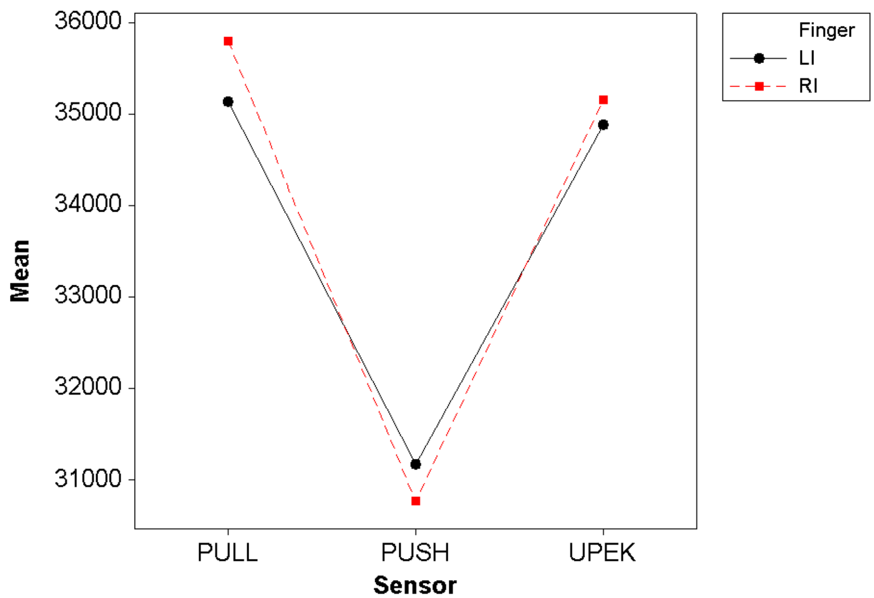


Figure 111 Finger*Sensor interaction plot of mean fingerprint image size for matching visit 3.

Results of the Tukey pairwise comparison test are presented in Table 63, which revealed that fingerprint image size was significantly different for each sensor comparison. Examining the interaction plot (Figure 111) and descriptive statistics (Table 62), we see that that the PULL sensor captured fingerprint images with the largest mean and median image size compared to the other two swipe-based sensors for the matching visit 3 DCC.

Table 63 Matching visit 3 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0000	-
UPEK	p = 0.0008	p = 0.0000

Table 64 Fingerprint area descriptive statistics by sensor for matching visit 3.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1691	35016	35840	3456	17920	41216
PUSH	1659	30964	30464	3789	20480	40192
PULL	1697	35464	36096	3489	21760	43264
LA	1700	70460	71936	8230	42752	87040

Concluding the analysis for fingerprint image area for matching visit 3, there was a significant difference between all sensor comparisons. In particular, the PULL sensor reported the largest improvement in mean image area from the DCCs thus far compared to the UPEK sensor. Examining the size improvements, as participants increased their usage with the PULL sensor, the mean image size also continued to increase compared to the UPEK sensor. However, these results are not generalizable and pertain to the population in this study only.

4.3.3.3.1.6. Hypothesis Testing Summary: Fingerprint Image Area

The hypothesis for the fingerprint image size that was evaluated for both index fingers and each of the five data collection components: training, enrollment, matching 1, matching 2, and matching 3 was stated as:

The PUSH or PULL sensor will be significantly different in terms of the size or area of the fingerprint in a swipe-based fingerprint image collected in each data collection component for all hand and finger sizes compared to the commercial UPEK sensor.

Results for the fingerprint image area statistical tests revealed there was no statistical difference in the main effect for the finger used in all DCC, however there was a significant main effect of sensor type. An interaction effect was also present in all DCC except for training. The interaction effect of finger*sensor revealed an interesting pattern across the swipe sensors; PULL and UPEK RI reported larger mean area sizes, whereas the LI of PUSH reported a larger mean image size. While the pattern of the interaction between the fingers and sensors was consistent, a cause cannot be determined at this time, but it would be interesting to further investigate. Tukey post hoc tests revealed differences in the mean fingerprint image size for the PUSH-PULL and PUSH-UPEK sensor pairs in all five data collection components. However, the UPEK-PULL comparison revealed no statistical difference for the training, enrollment, or matching visit 1 data collection component, however the PULL sensor reported larger mean and median image sizes. The Tukey post hoc analysis did report a statistical difference during matching visit 2 and 3 DCC between the PULL and UPEK, with the descriptive statistics indicating the PULL sensor captured a larger mean image size. Conclusions from the data analysis of fingerprint image size suggest the design of the PULL sensor may aid in capturing the largest fingerprint image area, while the PUSH may assist in capturing a smaller fingerprint image area than both the UPEK or PULL form factors. However, this conclusion only pertains to this study and is not generalizable. Table 43 summarizes the statistical testing for fingerprint image area.

Table 65 Summary of statistical testing for fingerprint image size or area.

	p-value			Post Hoc Analysis	Result
Data Collection Component (DCC)	Finger	Sensor	Finger*Sensor	Tukey Pairwise Comparison	Sensor Hypothesis Test (α = 0.05)
Training	0.344	0.000	0.349	UPEK = PULL	Accept
Enrollment	0.991	0.000	0.000	UPEK = PULL	Accept
Matching V1	0.830	0.000	0.000	UPEK = PULL	Accept
Matching V2	0.167	0.000	0.002	All pairwise differences significant	Accept
Matching V3	0.083	0.000	0.000	All pairwise differences significant	Accept

4.3.3.3.2. Fingerprint image contrast

The fourth metric of the HBSI evaluation method that is discussed is fingerprint image contrast, which is the last measure of image quality and ergonomics. Fingerprint image contrast measures how much contrast variation exists within the fingerprint area of the image. The measurement compares the sigma of the gray levels in each fingerprint image that was collected on each sensor. This measurement, like the fingerprint image area, only measures the area containing the fingerprint ridges and valleys, not the background area. Figure 112 shows three fingerprint images from the UPEK sensor with different image contrast variations.

Figure 112 Example fingerprint images from the UPEK sensor showing variations in image contrast values.

This measure is of importance to the HBSI as image contrast is a measure of within image variability directly resulting from how users interact with fingerprint sensors. One possible measure of this is inconsistent contact. For example, if a sensor design forces a user to lift their finger prematurely from the sensor, segments of the fingerprint area may be acceptable with other parts possibly being too light, which can cause problems for algorithms. Therefore, this measure investigates how users interact with sensors to evaluate if a particular fingerprint sensor design aids the collection of images with minimal variations in the gray levels (0-255). From a statistical standpoint, the test examined if the mean variability (sigma) was the same across the three swipe sensors.

The hypothesis for the fingerprint image contrast that was evaluated for both index fingers and each of the five data collection components: training, enrollment, matching 1, matching 2, and matching 3 was stated as:

> The PUSH or PULL sensor will be significantly different in terms of image contrast (reported gray level) in a swipe-based fingerprint image collected in

each data collection component for all hand and finger sizes compared to the commercial UPEK sensor.

To investigate the hypothesis for the fingerprint image contrast in each data collection component, the statistical process that was discussed in the previous 3 sections was followed. The assumptions of the Analysis of Variance (ANOVA) test held and are shown in Appendix W for each data collection component.

4.3.3.3.2.1. Fingerprint Image Contrast Results for Training

The hypothesis for fingerprint image contrast for the fingerprint images collected with the swipe sensors during training was stated as:

The PUSH or PULL sensor will be significantly different in terms of image contrast (reported gray level) for the swipe fingerprint images collected during training for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image contrast was different between the three swipe-based sensors and two fingers. The results showed a main effect of finger used, $F(1,2064) = 10.15$, $p = 0.001$. The main effect of form factor type was significant $F(2,2064) = 21.70$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,2064) = 0.58$, $p = 0.562$. Results of the Tukey pairwise comparison test are presented in Table 66 and reveal that there were statistical differences across all swipe sensor comparisons. Table 67 provides the descriptive statistics for all the tested sensors to provide additional insight on the training data. While the post hoc analysis revealed that all sensor pairs were different, the descriptive statistics show that the PUSH sensor had the lowest mean image contrast, followed by the PULL sensor, and finally the commercial UPEK sensor.

Table 66 Training Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0007	-
UPEK	p = 0.0099	p = 0.0000

Table 67 Fingerprint contrast descriptive statistics by sensor for training.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	696	44.421	48.267	11.897	12.227	60.963
PUSH	682	40.723	43.095	10.093	14.528	65.688
PULL	692	42.784	45.178	9.206	13.985	58.503
LA	694	48.07	49.716	8.575	26.827	63.605

Concluding the analysis for fingerprint image contrast for training, there was a significant difference between all sensor combinations. In particular, the PUSH and PULL sensors reported lower mean sigma values (image contrast) compared to the UPEK sensor. However, these results are not generalizable and pertain to the population in this study only.

4.3.3.3.2.2. Fingerprint Image Contrast Results for Enrollment

The hypothesis for fingerprint image contrast for the fingerprint images collected with the swipe sensors during enrollment was stated as:

> The PUSH or PULL sensor will be significantly different in terms of image contrast (reported gray level) for the swipe fingerprint images collected during enrollment for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The results showed a main effect of finger used, $F(1,5164) = 0.00$, $p = 0.000$. The main effect of form factor type was significant $F(2,5164) = 37.04$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,5164) = 1.82$, $p = 0.163$. Results of the Tukey pairwise comparison test are presented in Table 68, which revealed that fingerprint image size was significantly different for each sensor type, except for those captured with the UPEK and PULL sensors. Table 69 provides the descriptive statistics for all the tested sensors to provide additional insight on the enrollment data. The enrollment descriptive statistics again reveal that the PUSH and PULL sensors have lower mean sigma values (image contrast) than the UPEK sensor. In addition, the standard deviation in the data collected is lower for both fabricated sensors compared to the UPEK, suggesting that the design of the sensor is aiding in the collection of fingerprint images of lower gray level variability.

Table 68 Enrollment Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0000$	-
UPEK	$p = 0.0006$	$p = 0.0000$

Table 69 Fingerprint area descriptive statistics by sensor for enrollment.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1735	42.215	45.818	12.491	13.551	63.59
PUSH	1695	38.976	40.61	10.308	12.16	66.815
PULL	1740	40.824	43.767	10.176	12.243	60.171
LA	1740	46.988	48.059	8.752	22.238	63.204

Concluding the analysis for fingerprint image contrast for enrollment, there was a significant difference between all sensor combinations. Of interest was the PUSH and PULL sensors, which reported lower mean sigma values (image contrast) compared to the UPEK sensor. However, these results are not generalizable and pertain to the population in this study only.

4.3.3.3.2.3. Fingerprint Image Contrast Results for Matching visit 1

The hypothesis for fingerprint image contrast for the fingerprint images collected with the swipe sensors during the matching visit 1 DCC was stated as:

> The PUSH or PULL sensor will be significantly different in terms of image contrast (reported gray level) for the swipe fingerprint images collected during matching visit 1 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results showed a main effect of finger used, $F(1,5151) = 4.46$, $p = 0.035$. The main effect of form factor type was significant $F(2,5151) = 0.000$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,5151) = 0.37$, $p = 0.689$. Results of the Tukey pairwise comparison test are presented in Table 70, which revealed that the gray level variability (mean sigma value) of the fingerprint images was significantly different for each sensor type, except for those captured with the UPEK and PULL sensors. Note the reported *p*-value for the PULL-UPEK comparison is 0.0605, which was close to the significance level (α = 0.05). Table 71 provides the descriptive statistics for all the tested sensors to provide additional insight on the matching visit 1 data. Investigating the data the PUSH sensor reported the lowest mean image contrast variation. The standard deviation, or variability, of image contrast was 10.5 for both the PUSH and PULL sensors, but more spread for the commercial UPEK sensor, indicating the UPEK produced images of greater gray level variability.

Table 70 Matching visit 1 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	p = 0.0000	-
UPEK	p = 0.0605	p = 0.0000

Table 71 Fingerprint area descriptive statistics by sensor for matching visit 1.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1730	40.781	44.237	12.609	12.152	63.155
PUSH	1687	37.524	38.602	10.516	13.299	62.697
PULL	1740	39.912	42.86	10.526	12.622	59.393
LA	1740	46.384	47.288	8.871	22.267	62.666

Concluding the analysis for fingerprint image area for matching visit 1, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK. Moreover, examining the descriptive statistics, the PUSH sensor reported a lower within image variability in terms of image contrast than the UPEK for the data in this study, but is not generalizable to other populations.

4.3.3.3.2.4. Fingerprint Image Contrast Results for Matching visit 2

The hypothesis for fingerprint image contrast for the fingerprint images collected with the swipe sensors during the matching visit 2 DCC was stated as:

> The PUSH or PULL sensor will be significantly different in terms of image contrast (reported gray level) for the swipe fingerprint images collected during matching visit 2 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results showed a main effect of finger used, $F(1,5019) = 10.88$, $p = 0.001$. The main effect of form factor type was significant $F(2,5019) = 60.79$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,5019) = 0.58$, $p = 0.561$. Results of the Tukey pairwise comparison test are presented in Table 72, which revealed that fingerprint image size was significantly different for each sensor comparison, except PULL and UPEK. Examining the descriptive statistics (Table 73), we see that that the PULL sensor had the lowest variability (sigma), thus aided in the capturing of the most consistent images in terms of variability in gray levels compared to the other two swipe-based sensors for the matching visit 2 DCC.

Table 72 Matching visit 2 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0000$	-
UPEK	$p = 0.4590$	$p = 0.0000$

Table 73 Fingerprint area descriptive statistics by sensor for matching visit 2.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1677	41.646	44.32	11.798	12.913	63.139
PUSH	1670	37.989	39.464	10.125	12.654	66.487
PULL	1678	41.217	43.803	9.391	14.316	57.572
LA	1700	46.117	47.319	9.052	22.531	63.604

Concluding the analysis for fingerprint image area for matching visit 2, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK. Moreover, examining the descriptive statistics, the PUSH sensor reported a lower within image variability in terms of image contrast than the UPEK for the data in this study, which as reported before is not generalizable to other populations.

4.3.3.3.2.5. Fingerprint Image Contrast Results for Matching visit 3

The hypothesis for fingerprint image contrast for the fingerprint images collected with the swipe sensors during the matching visit 3 DCC was stated as:

> The PUSH or PULL sensor will be significantly different in terms of image contrast (reported gray level) for the swipe fingerprint images collected during matching visit 3 for all hand and finger sizes compared to the UPEK sensor.

A two-factor ANOVA was performed at α of 0.05 to determine whether the mean fingerprint image area was different between the three swipe-based sensors and two fingers. The two-factor ANOVA results showed no main effect of finger used, $F(1,5041) = 0.02$, $p = 0.895$. The main effect of form factor type was significant $F(2,5041) = 40.80$, $p = 0.000$. There was no significant interaction between finger and sensor, $F(2,5041) = 1.24$, $p = 0.289$. Results of the Tukey pairwise comparison test are presented in Table 74, which revealed that fingerprint image size was significantly different for all sensor comparisons except UPEK and PULL. Examining the descriptive statistics (Table 75), we see that that the PULL and PUSH sensors had lower standard deviations or variability in terms of image contrast, yet the difference in means for the PULL and UPEK were not significant for the matching visit 3 DCC.

Table 74 Matching visit 3 Tukey pairwise comparison results for form factor type.

	PULL	PUSH
PUSH	$p = 0.0000$	-
UPEK	$p = 0.1704$	$p = 0.0000$

Table 75 Fingerprint area descriptive statistics by sensor for matching visit 3.

Sensor	N	Mean	Median	StDev	Min.	Max.
UPEK	1691	40.594	43.566	11.837	11.97	61.926
PUSH	1659	37.487	38.867	9.736	13.5	57.063
PULL	1697	39.946	42.343	9.723	12.739	58.625
LA	1700	46.793	47.923	8.666	22.696	61.619

Concluding the analysis for fingerprint image contrast for matching visit 3, there was a significant difference between the PUSH/PULL and PUSH/UPEK sensors, but no statistical differences were found between the PULL and UPEK. Moreover, examining the descriptive statistics, the PUSH sensor again reported a lower within image variability in terms of image contrast than the UPEK for the data in this study, but is not generalizable to other populations.

4.3.3.3.2.6. Hypothesis Testing Summary: Fingerprint Image Contrast

The hypothesis for the fingerprint image contrast that was evaluated for both index fingers and each of the five data collection components: training, enrollment, matching 1, matching 2, and matching 3 was stated as:

> The PUSH or PULL sensor will be significantly different in terms of image contrast (reported gray level) in a swipe-based fingerprint image collected in each data collection component for all hand and finger sizes compared to the commercial UPEK sensor.

Results for the fingerprint image contrast statistical tests revealed there was no statistical difference in the main effect for the finger used in all DCC, however there was a significant main effect of sensor type. An interaction effect was also not present in each DCC. Tukey post hoc tests revealed statistical differences in the mean fingerprint image contrast for the PUSH/PULL and PUSH/UPEK sensor pairs in all five data collection components. However, the UPEK/PULL comparison revealed statistical differences for the training and enrollment DCC, but did not for the three matching DCCs, with the PULL mean sigma value being lower than UPEK's. The PUSH sensor resulted in the lowest mean image contrast score, as well as the lowest standard deviation in all DCCs, meaning the fingerprint images collected in each DCC had the lowest within image variability (measured gray levels). Conclusions from the data analysis of fingerprint image contrast suggest the design of the PUSH sensor may aid users in maintaining more consistent contact with the sensor resulting in fingerprint images which contain a more consistent mean gray level value (sigma).

According to the results, the PULL sensor was next best, followed by the UPEK sensor. Table 76 summarizes the statistical testing for fingerprint image contrast.

Table 76 Summary of statistical testing for image contrast.

	p-value			Post Hoc Analysis	Result
Data Collection Component (DCC)	Finger	Sensor	Finger*Sensor	Tukey Pairwise Comparison	Sensor Hypothesis Test (α = 0.05)
Training	0.001	0.000	0.562	All pairwise differences significant	Accept
Enrollment	0.000	0.000	0.163	All pairwise differences significant	Accept
Matching V1	0.035	0.000	0.689	UPEK = PULL	Accept
Matching V2	0.001	0.000	0.561	UPEK = PULL	Accept
Matching V3	0.895	0.000	0.289	UPEK = PULL	Accept

4.4. Usability

The next component of the HBSI evaluation method (Figure 90) that will be discussed is usability. Both qualitative and quantitative data were collected to understand usability from two distinct perspectives. The qualitative measure for usability on the three swipe-based sensors was a user satisfaction survey, which was based on Lewis's Post-Study System Usability Questionnaire (PSSUQ) (1993). The quantitative data for usability included measurements of efficiency, learnability, and effectiveness. Efficiency examined task time. Learnability examined if participants completed the task, the level of effort needed to complete it, and the amount of assistance they needed to complete the task. Effectiveness examined how well the participants interacted with the sensors, which in this document is discussed under biometric performance, specifically the Failure to Acquire section.

4.4.1. HBSI Post-Study System Usability Questionnaire (HBSI PSSUQ)

As discussed in 2.8.4.1.1.1, a modified version of Lewis's PSSUQ (1993) was administered electronically after the matching visit 3 DCC was complete to determine if participants found one of the swipe-based sensors more usable. The instructions, HBSI questionnaire, and the original questions found in Lewis (1993) can be found in Appendix A. From the 85 participants, only one participant did not complete the survey, resulting in a survey completion rate of 98.82%. The participant was emailed and asked to finish the survey, but no response was received. The PSSUQ scores for each scale and subscale were calculated by taking the average of the items listed in Table 77. If an item was listed as N/A, the average of the remaining scores was used.

Table 77 PSSUQ score calculation rules (Lewis, 1993).

Scale	Average responses to:
Overall	Items 1 – 19
SYSUSE	Items 1 – 8
INFOQUAL	Items 9 – 15
INTERQUAL	Items 16 – 18

An ANOVA test was used to evaluate each part of the HBSI survey because the participant response scores met the ANOVA model assumptions for the HBSI post-study usability questionnaire, which can be found in Appendix X. The results of the parts of the questionnaire: overall satisfaction, system usefulness (SYSUSE), information quality (INFOQUAL), and interface quality (INTERQUAL) are outlined in the following sections. The hypothesis under test for each part of the questionnaire was: The new form factor(s) will be significantly different in terms of the scores for overall satisfaction, SYSUSE, INFOQUAL, and INTERQUAL than the commercially available form factor.

4.4.1.1. HBSI PSSUQ Results for Overall User Satisfaction Score

The first metric of the usability questionnaire was the overall user satisfaction score. This score was computed by taking the average of all 19 items. The lower the score, the more satisfied users are with the system. Scores ranged from 1 to 7, which were based on the seven point Likert scale. The hypothesis evaluated the overall usability score for the three swipe-based sensors. The results revealed that there was a statistically significant difference in the overall usability score by form factor type, $F(2,249) = 12.34$, $p = 0.000$ at an α of 0.05, thus rejecting the null hypothesis. In order to test for differences in usability scores for the three swipe sensors, the Tukey test for pairwise comparisons was conducted, which revealed differences in overall usability scores for UPEK and PUSH, as well as PULL and PUSH, but no differences in the overall usability scores for UPEK and PULL (Table 78). The descriptive statistics are listed in Table 79. Investigating the mean overall user satisfaction score, the PUSH reported the lowest mean score (2.49). While the PULL and UPEK reported no statistical difference in the post hoc analysis, the UPEK (1.76) had a lower mean score than the PULL (2.00) did. However as mentioned in previous sections, it was not possible to test the effects prior usage of the UPEK sensor had on the results of the questionnaire.

Table 78 HBSI PSSUQ overall Tukey pairwise comparison results for form factor type.

	PUSH	PULL
UPEK	$p < 0.05$	*n.s.*
PUSH	-	$p < 0.05$

Table 79 HBSI PSSUQ overall descriptive statistics.

Sensor	N	Mean	Median	StDev	Min	Max
UPEK	84	1.7596	1.5132	0.8058	1	4.3158
PUSH	84	2.486	2.237	1.093	1	5.263
PULL	84	1.995	1.737	0.981	1	5.579

4.4.1.2. HBSI PSSUQ Results for System Usefulness (SYSUSE)

The second metric of the usability questionnaire was the system usefulness score. This score was computed by taking the average of questionnaire items one through eight. Again, the lower the score, the more satisfied users are with the system, with scores ranging from 1 to 7. The hypothesis evaluated the system usefulness score for the three swipe-based sensors. The results revealed that there was a statistically significant difference in system usefulness for the different form factor type, $F(2,249) = 22.61$, $p = 0.000$ at an α of 0.05, thus rejecting the null hypothesis. In order to test for differences in system usefulness for the three form factors, the Tukey test for pairwise comparisons was conducted, which revealed differences for all the sensors (Table 80). The descriptive statistics are listed in Table 81. Investigating the mean SYSUSE scores, we see the UPEK (1.55) was most useful, followed by the PULL (2.07), and PUSH (2.73), respectively. Again, the impact of participant's prior usage of the UPEK sensor on this questionnaire could not be quantified.

Table 80 HBSI PSSUQ SYSUSE Tukey pairwise comparison results for form factor type.

	PUSH	PULL
UPEK	$p < 0.05$	$p < 0.05$
PUSH	-	$p < 0.05$

Table 81 HBSI PSSUQ SYSUSE descriptive statistics.

Sensor	N	Mean	Median	StDev	Min	Max
UPEK	84	1.5527	1.125	0.8405	1	5.25
PUSH	84	2.731	2.625	1.381	1	6.5
PULL	84	2.066	1.75	1.13	1	6.375

4.4.1.3. HBSI PSSUQ Results for Information Quality (INFOQUAL)

The third metric of the usability questionnaire was the information quality score. This score was computed by taking the average of questionnaire items nine through fifteen. Again, the lower the score, the more satisfied users are with the system, with scores ranging from 1 to 7. The hypothesis evaluated the information quality of each form factor type. The results showed no statistically significant difference in information quality for the different form factor type, $F(2,249) = 1.89$, $p = 0.153$ at an α of 0.05, therefore we fail to reject the null hypothesis. The descriptive statistics are listed in Table 81. While the statistical test reported no differences in information quality scores by form factor type, the PULL (1.77) had the lowest mean score, followed by the PUSH (1.90), and UPEK (2.03). Furthermore, while the PUSH and PULL received a better mean score than the UPEK, no statistical difference was found, which as mentioned in earlier sections, may have been due to participants prior experiences and biases with the UPEK sensor.

Table 82 HBSI PSSUQ INFOQUAL descriptive statistics.

Sensor	N	Mean	Median	StDev	Min	Max
UPEK	84	2.037	1.857	0.95	1	4.857
PUSH	84	1.9075	1.8571	0.7866	1	4
PULL	84	1.7742	1.4286	0.8801	1	5.7143

4.4.1.4. Interface quality (INTERQUAL)

The last metric of the usability questionnaire was the interface quality score. This score was computed by taking the average of questionnaire items sixteen through eighteen. Again, the lower the score, the more satisfied users are with the system, with scores ranging from 1 to 7. The hypothesis evaluated the interface quality score for the three swipe-based sensors. The results revealed that there was a statistically significant difference in interface quality for the different form factor type, $F(2,249) = 22.35$, $p = 0.000$ at an α of 0.05, thus rejecting the null hypothesis. In order to test for differences in interface quality for the three form factors, the Tukey test for pairwise comparisons was conducted, which revealed differences for all the sensors (Table 83). The descriptive statistics are listed in Table 84. Analyzing the mean INTERQUAL scores, the data reveals the UPEK (1.70) was most efficient, followed by the PULL (2.25), and PUSH (3.00), respectively.

Table 83 PSSUQ INTERQUAL Tukey pairwise comparison results for form factor type.

	PUSH	PULL
UPEK	$p < 0.05$	$p < 0.05$
PUSH	-	$p < 0.05$

Table 84 PSSUQ INTERQUAL descriptive statistics.

Sensor	N	Mean	Median	StDev	Min	Max
UPEK	84	1.699	1.333	0.974	1	6
PUSH	84	2.992	2.667	1.564	1	7
PULL	84	2.245	2	1.162	1	6

4.4.1.5. User comments during the HBSI post-study questionnaire

After completing the 19 item questionnaire, participants were given an opportunity to type their comments, feedback, or thoughts regarding the study and the sensors used. Appendix Y contains all user feedback and comments. The following comments in Table 85 provide some insight to what the participants stated.

Table 85 Participant feedback excerpts from the HBSI post-study questionnaire.

Type	Comment
General	
	• I liked the ramp effect of the UPEK. I think if the PULL sensor was angled I would like it much better because the channel combined with the angle would be more effective and comfortable. The PUSH sensor seemed to work pretty well. I don't think an angle on it would be effective, but, again, the channel was very helpful.
UPEK Favorable	
	• I felt like the UPEK had a clearer image, I did not have as many problems scanning with it, than with the others (Push and Pull).
	• I liked how the UPEK sensor was curved. It made it easier to swipe your finger. The PULL sensor was my least favorite because it was not curved so it was harder to pull my finger across it. The PULL sensor was a little uncomfortable. I liked the PUSH sensor because it was easy to understand, and it was comfortable to use.
	• UPEK and PULL were very similar, though I preferred [preferred] the slight curvature and smooth feel of the UPEK. The PUSH sensor felt odd when pushing my finger over the sensor.
UPEK Unfavorable	
	• For the UPEK, it is a little confusing, I can not [cannot] remember whether to swipe the finger or put the finger on the sensor for a while. The PUSH sensor, it is a little uncomfortable [uncomfortable]. PULL sensor is best!
	• Upek : It had an attractive design and also was very comfortable to use. I guess the only issue was if it had a visual sign to tell us which direction to swipe (like in the PUSH & PULL). Once I knew the direction, it was very easy to use.PUSH: was bulky and it felt very odd to push my finger away from me.PULL: was bulky but at least more comfortable since I was pulling my finger towards me.
	• The visual cues of the upek were not very clear though I found it to be the most pleasant to use.
PUSH/PULL Favorable	
	• UPEK didn't always register the swipes as well as the PUSH or PULL, PUSH always felt comfortable to use even though I thought the PULL would be the easiest to use
	• The Push/Pull sensors are nice because they help channel your finger over the scanner. The Push doesn't function like I would immediately expect a fingerprint scanner to, but I liked it best in the end.
	• The arrows on the PUSH and PULL are helpful if someone weren't shown a demonstration on how to use them before trying it. The UPEK doesn't have that feature and it could be confusing if a user didn't know to start with their finger on the blue dots.
PUSH/PULL Unfavorable	
	• Sometimes I have to think a while to distinguish between the push and pull sensor. For some reason, I think the colored dots made it confusing. Maybe having just the arrows would be enough.
	• Pushing was awkward to do. The arrows are really helpful. The UPEK had a natural feel when you pull upwards and back.

4.4.1.6. <u>Hypothesis Testing Summary: HBSI user satisfaction questionnaire</u>

The hypotheses under test for the user satisfaction questionnaire were: The new form factor(s) will be significantly different in terms of the scores for overall satisfaction, SYSUSE, INFOQUAL, and INTERQUAL than the commercially available form factor.

The overall user satisfaction results revealed no statistical difference between the UPEK and PULL, with the PUSH receiving the worst mean score. This was interesting to analyze as the UPEK and PULL are both “pull”-type sensors, which many of the participants had used prior to this study, compared to the PUSH sensor design, which none of the participants had experienced prior to this study.

Regarding the system usefulness and interface quality metrics, both statistical tests showed a difference amongst the three swipe-based sensors, with the UPEK receiving the lowest (best) score, compared to the PUSH and PULL designed sensors. It is interesting to note that these components of the HBSI PSSUQ may have been influenced by participants’ prior experience with the UPEK sensor, as the questions dealt with comfort, pleasantness, likeability, and functionality.

Lastly, the INFOQUAL results revealed that there was no statistical difference across the three swipe-based sensors (p = 0.153) at a significance level (α) of 0.05. However, the PULL and PUSH sensors received lower (better) scores than the UPEK. Table 86 summarized the results of the HBSI PSSUQ.

Table 86 Summary results of the HBSI PSSUQ.

HBSI PSSUQ Scale	Mean UPEK	PUSH	PULL	Result of Hypothesis Test	Post Hoc Analysis
Overall	1.76	2.49	2	Accept	UPEK = PULL
SYSUSE	1.55	2.73	2.07	Accept	All pairwise differences significant
INFOQUAL	2.03	1.91	1.77	Reject	-
INTERQUAL	1.7	3	2.25	Accept	All pairwise differences significant

In summary, this questionnaire provided a valuable component to further understand the human component in biometric systems. However, as stated earlier in the demographics section, a majority of the participants had previously used the UPEK sensor, possibly compromising the validity of this survey instrument due to the experimental design that recruited participants who previously used the UPEK swipe-based fingerprint sensor. For more discussion on this, please see the recommendations for future research section.

4.4.2. Efficiency

The next measure of usability is the measure of efficiency, or how long did it take participants to complete each data collection component on each sensor for the left and right index finger, which was measured in seconds. This metric for efficiency examined whether the design of the form factor allowed the user to interact with a particular sensor design more efficiently in terms of time to complete the task than another. The hypothesis under test was stated as:

> The PUSH or PULL sensor will be significantly different in terms of the amount of time a user requires to complete the task than with the commercial UPEK or Large Area (LA) sensor.

The Kruskal-Wallis (KW) test for equality in medians was used due to the model assumptions of ANOVA not being met, as shown in Appendix Z. In addition, each data collection component only had an $N \leq 85$ (due to FTEs), therefore the Central Limit Theorem did not hold for this analysis either. Thus, the non-parametric tests were conducted for each data collection component and are now discussed.

First, a visual analysis of the data was conducted to see where participants with lengthy task times occurred (potential outliers), which are shown in Appendix AA for each DCC. The statistical software used was Minitab® 15, which classified observations as outliers on the boxplots that were at least 1.5 times the interquartile range (Q3 – Q1). Using this methodology, tasks that took longer than approximately 40 seconds to complete for training, approximately 60 seconds for enrollment, and approximately 50 seconds to complete each of the three matching visits were classified as extreme observations.

Second, the Kruskal-Wallis test was performed for each mode and the results are shown below in Table 87. All *p* values were compared to the significance value (α) of 0.05, thus we reject the null hypothesis for each DCC, as the medians are not all the same.

Table 87 Results of the Kruskal-Wallis tests for task time.

DCC	*H* statistic and *p* value
Training	$H(7) = 106.69$, $p = 0.000$
Enrollment	$H(7) = 74.82$, $p = 0.000$
Matching V1	$H(7) = 82.65$, $p = 0.000$
Matching V2	$H(7) = 117.27$, $p = 0.000$
Matching V3	$H(7) = 118.15$, $p = 0.000$

However, the Kruskal-Wallis test does not illustrate where the differences in medians were, thus an investigation into the descriptive statistics is warranted, which are shown in Table 88. Since the hypothesis under test stated the PUSH or PULL would significantly reduce the task time compared to the UPEK and LA, those descriptive statistics were analyzed. First, task times and standard deviation values were expected to be inflated during the training and enrollment DCC, due this being participants' first experience interacting with a "push"-based swipe motion. However, comparing the mean task time across the four sensors, there was a small delta for mean task time, but the standard deviation was inflated by 1.5 to 2 times.

Analyzing the data over enrollment and the 3 matching visits the mean task times stay consistent across all four sensors. More interesting was the change in standard deviation values. First, the PUSH sensor had significant improvements in matching visit 3 compared to the earlier DCCs. Secondly, the standard deviation values for the UPEK and LA sensors varied over the course of the test, which was interesting to note as many of the participants had used those two devices prior to this study. Lastly, the PULL sensor revealed the smallest delta in standard deviation values over the five tested data collection components, indicating the participants' task time was most consistent.

In summary, while conclusions from the hypothesis could not formally be made, the PUSH and PULL sensors both showed interesting results that warrant further investigation.

Table 88 Summary descriptive statistics for task time by DCC.

	Training		Enrollment		Matching V1		Matching V2		Matching V3		Overall	
Sensor	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
UPEK_RI	23.89	11.74	43.34	19.64	39.03	11.92	38.83	14.54	36.23	9.67	36.26	13.50
UPEK_LI	19.83	13	39.05	10.34	36.18	7.84	34.86	10.27	35.63	12.5	33.11	10.79
PUSH_RI	32.3	25.91	48.09	26.1	46.28	34.49	41.96	20.36	38.57	16.59	41.44	24.69
PUSH_LI	23.7	22.34	43.56	24.04	37.09	10.47	36.55	15	35.59	16.51	35.30	17.67
PULL_RI	25.1	15.15	40.52	12.9	37.81	10.74	36.75	8.98	36.88	13	35.41	12.15
PULL_LI	21.02	14.88	40.33	12.26	38.09	12.24	36.43	12.05	36.26	15.66	34.43	13.42
LA_RI	26.96	7.37	48.45	11.22	43.65	8.68	45.79	10.06	43.43	7.24	41.66	8.91
LA_LI	21.04	6.13	44.03	7.42	42.08	7.76	45.15	26.37	40.72	6.79	38.60	10.89

4.4.3. Learnability

The second quantitative metric in the HBSI evaluation method (Figure 90) for usability is learnability. Learnability consisted of three measurements: completeness, or task completion; maximum user effort (MUE); and the number of assists. The next three sections discuss the three measurements of learnability by the five data collection components: training, enrollment, matching visit 1, 2, and 3.

4.4.3.1. Task Completion

Completeness was defined for this study as the sequence of events required to complete the overall task from for each finger/sensor/visit combination. Task completion had two different metrics in this study, one for training, and the other for enrollment and the three matching visits.

4.4.3.1.1. Training Task Completion

Task completion for training was defined for a participant when four images were successfully acquired for a particular finger and sensor combination. Task completion for training resulted in 6 individuals that could not provide 4 images for the following sensor and finger: PUSH LI (2), PULL LI (1), PUSH RI (2), and UPEK LI (1).

4.4.3.1.2. Task Completion for Enrollment and Matching

Task completion for the remaining four data collection components: enrollment and matching visit 1, 2, and 3 were defined the same. Completion consisted of a participant successfully acquiring 10 images for a particular finger and sensor combination. Table 89 shows the participants by sensor, DCC, and finger that did not complete the task. Also, for the matching completion calculation, participants who produced an FTE were included as part of this metric, even though they did not interact with the sensors.

Table 89 Number of participants who did not complete the task for enrollment and matching by sensor and finger.

	UPEK		PUSH		PULL		LA	
Data collection component	LI	RI	LI	RI	LI	RI	LI	RI
Enrollment	0	1	4	2	0	0	0	0
Matching V1	0	1	3	4	1	0	0	0
Matching V2	2	2	4	2	2	1	0	0
Matching V3	0	1	4	2	1	0	0	0

4.4.3.1.3. Task Completion Rate Summary

Examining all five data collection components for the task completion rate, the large area sensor had the highest task completion rate (100%) when all data collection components and fingers were combined, followed by the PULL (99.6%) and UPEK (99.1%). The worst performing in terms of task completion rate was the PUSH, which had a rate of 96.6%. Although the PUSH sensor had the worst task completion rate, this was the participants' first encounter with a "push"-type interaction, compared to the "pull"-based interaction the UPEK and PULL sensors required. Results show a delta of only 3% across the sensor, which shows potential for the PUSH sensor and warrants further investigation. Table 90 shows the task completion rates for the four sensors across the five data collection components, as well as the total average for each sensor.

Table 90 Task completion rates for the 4 sensors over the data collection components.

	UPEK		PUSH		PULL		LA	
Sensor	LI	RI	LI	RI	LI	RI	LI	RI
Training	98.8%	100.0%	97.6%	97.6%	98.8%	100.0%	100.0%	100.0%
Enrollment	100.0%	98.8%	95.3%	97.6%	100.0%	100.0%	100.0%	100.0%
Match V1	100.0%	98.8%	96.5%	95.3%	98.8%	100.0%	100.0%	100.0%
Match V2	97.6%	97.6%	95.3%	97.6%	97.6%	98.8%	100.0%	100.0%
Match V3	100.0%	98.8%	95.3%	97.6%	98.8%	100.0%	100.0%	100.0%
Total (Avg)	99.28%	98.80%	96.00%	97.14%	98.80%	99.76%	100%	100%

4.4.3.2. Maximum User Effort

Maximum user effort, or MUE, is a metric that compares the proportion of presentations needed to enroll/match on a particular sensor to the maximum number of interaction presentations allowed for that particular segment of the test. This was reported by sensor/visit/finger combination. MUE had two different metrics in this study, one for training, and the other for enrollment and the three matching visits.

4.4.3.2.1. Training MUE

MUE for training was defined for a participant as the amount of effort needed to acquire the four images for a particular finger and sensor combination. A maximum of 15 presentations were allowed during training for each finger/sensor. The data for training MUE (Figure 113) shows the breakdown of participants who required more effort to complete the task as outliers.

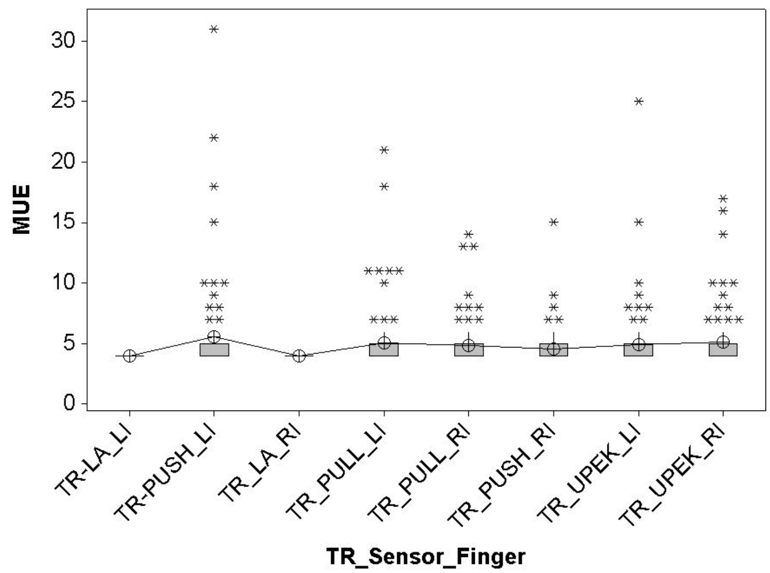


Figure 113 Box plot of MUE for training by sensor and finger.

4.4.3.2.2. MUE for Enrollment and Matching

MUE for the remaining four DCCs: enrollment and matching visit 1, 2, and 3 were defined the same. MUE was defined here as the amount of effort needed to acquire the 10 images for a particular finger and sensor combination. A maximum of 30 presentations were allowed during these four data collection components for each finger/sensor. Figure 114 shows the data for each of the four data collection components. Also, for the matching MUE calculation, participants who produced an FTE were included as part of this metric, even though they did not interact with the sensors. Participants who recorded FTEs or an attempt level FTA during Matching visit 1, 2, or 3 are listed as outliers at the zero point for the particular sensor/finger combination.

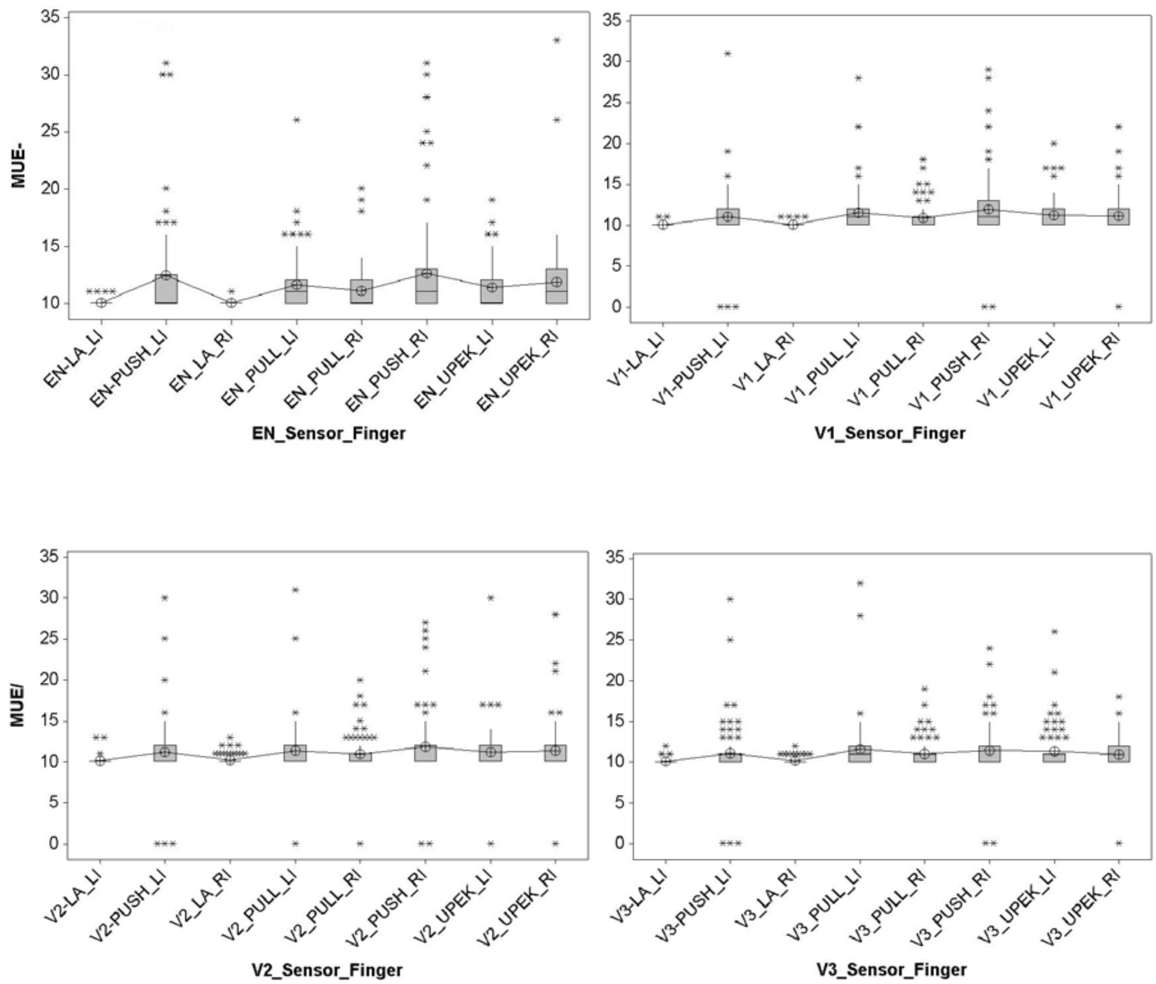


Figure 114 Box plot of MUE for enrollment and all three matching visits by sensor and finger.

4.4.3.2.3. MUE Summary

Examining all five data collection components for MUE, the large area sensor required the least amount of effort by the user to complete the task. While the PUSH sensor required the most user effort to complete the task on average during training and enrollment, the mean MUE for the PUSH improved during the remaining DCCs. This indicates participants that never had used a “push”-type interaction device decreased their level of effort to be comparable or better than with the UPEK or PULL sensor. However, certain individuals had problems with the PUSH sensor, resulting in a larger spread of the data, or standard deviation, during most of the DCCs. Further research is warranted to determine if the problematic users with the PUSH sensor were due to the design of the sensor or the acquisition algorithm, which was outside the scope of this study. Table 91 outlines the MUE average and standard deviations for all data collection components, sensors, and fingers.

Table 91 MUE mean and standard deviation by data collection component, sensor, and finger.

		Left Index		Right Index		Combined Average	
DCC	Sensor	Mean	StDev	Mean	StDev	Mean	StDev
Training	UPEK	4.929	2.755	5.141	2.527	5.035	2.641
	PUSH	5.529	4.067	4.565	1.467	5.047	2.767
	PULL	5.047	2.828	4.847	1.967	4.947	2.3975
	LA	4	0	4	0	4	0
Enrollment	UPEK	11.353	1.913	11.824	3.285	11.5885	2.599
	PUSH	12.412	4.779	12.624	4.693	12.518	4.736
	PULL	11.635	2.483	11.094	1.968	11.3645	2.2255
	LA	10.047	0.213	10.012	0.108	10.0295	0.1605
Matching V1	UPEK	11.212	1.915	11.282	2.13	11.247	2.0225
	PUSH	11.047	3.477	11.906	4.07	11.4765	3.7735
	PULL	11.494	2.644	10.824	1.597	11.159	2.1205
	LA	10.024	0.152	10.047	0.213	10.0355	0.1825
Matching V2	UPEK	11.165	2.878	11.376	3.128	11.2705	3.003
	PUSH	11.176	3.774	11.788	4.115	11.482	3.9445
	PULL	11.318	3.274	10.965	2.27	11.1415	2.772
	LA	10.082	0.468	10.224	0.564	10.153	0.516
Matching V3	UPEK	11.341	2.543	10.906	1.968	11.1235	2.2555
	PUSH	11.094	3.657	11.365	3.162	11.2295	3.4095
	PULL	11.565	3.227	10.976	1.669	11.2705	2.448
	LA	10.047	0.263	10.129	0.371	10.088	0.317

4.4.3.3. Assists

The last measure of learnability measured the number of assists the author gave to the participants if they could not complete the task without error or recall of proper interaction technique. Assists were defined as attempts, which the author provided an audio, visual, or physical cue to the participant. Assists were given if prompted by participant question (Appendix B), as well as if four consecutive erroneous interaction attempts took place.

Throughout the almost 34,000 interactions with the four sensors 197 assists were documented, which are outlined by sensor type, finger, and data collection component in Table 92. This table shows the training required the most assistance, followed by matching visit 2, enrollment, matching visit 3, and matching visit 1. One might find the data for matching visit 2 interesting in that it is the second highest, but recall that training, enrollment, and matching visit 1 all occurred in the first session and matching visit 2 occurred in the following week.

Table 92 Number and percentage of assists by sensor, finger, and DCC.

Data Collection Component	Sensor								Total	% of Assists
	UPEK		PUSH		PULL		Large Area			
	RI	LI	RI	LI	RI	LI	RI	LI		
Training	10	9	28	7	9	9	2	2	76	38.6%
Enrollment	12	1	13	4	7	2	0	0	39	19.8%
Matching V1	1	0	5	0	3	1	0	0	10	5.1%
Matching V2	15	0	12	8	7	9	0	0	51	25.9%
Matching V3	7	2	4	0	1	4	3	0	21	10.7%
Total	45	12	62	19	27	25	5	2		
Percentage	22.8%	6.1%	31.5%	9.6%	13.7%	12.7%	2.5%	1.0%		

Therefore examining the number of assists by the three visits or sessions, the number significantly decreases from 63.5% in visit 1, 25.9% in visit 2, and 10.7% in visit 3, indicating familiarity and habituation to the devices was occurring. Also, analyzing Table 92, it reveals that the PUSH required the most assistance, which may have been due to it requiring a different motion (habituation) than the other sensors and the experimental design. As mentioned in the previous sections, a number of participants had previously used a “pull”-based sensor similar to the UPEK and PULL sensors used in this study. Thus, participants had prior experience with the devices and should have known how to interact with the UPEK and PULL devices. On the contrary, none of the participants had previously used a “push’-based swipe sensor prior to this study. Therefore even though the experimental design was meant to be pseudo-random, the design was not balanced in terms of sensor type, as it included two “pull”-based sensors, 1 “push”-based sensor, and 1 placement sensor, potentially biasing results towards the “pull”-based sensors. In addition to the familiarity of the “pull”-based sensor over the “push”-based, note the right index values are higher than the left, which may indicate a habituation effect, as all participants started with their right hand, and on completion moved on to the task with the left hand. In the following paragraphs and tables, each assist type will be analyzed by sensor and finger.

The first assist category “flatten hand / open hand” was given almost exclusively to participants interacting with the PUSH sensor (Table 93). This was most likely to it requiring a different motion than the UPEK and PULL sensors. The main observation during this assistance was that participants that had the hand in a fist with the index finger extended could not keep the index in contact with the sensor during a “push” motion, but could with a “pull” as they could “flick” the fingertip, which was an undesired motion as well.

Table 93 “Flatten hand / open hand” assist analysis.

	UPEK		PUSH		PULL		LA	
DCC	RI	LI	RI	LI	RI	LI	RI	LI
Training	1	1	3	1	0	1	0	0
Enrollment	1	0	2	1	0	0	0	0
Matching Visit 1	0	0	0	0	0	0	0	0
Matching Visit 2	0	0	7	0	0	1	0	0
Matching Visit 3	0	0	2	0	0	0	0	0
Total	2	1	14	2	0	2	0	0

The second assist category is “Keep fingers straight (no curl/flick)”. This assist was given to participants who kept their finger either too bent or curled and could not keep consistent contact with the sensor, or when swiping “flicked” their fingertip instead of moving the entire finger. Table 94 shows that this assist was spread evenly over the three swipe-based sensors and occurred mainly in the training and enrollment DCCs.

Table 94 “Keep fingers straight (no curl/flick)” assist analysis.

	UPEK		PUSH		PULL		LA	
DCC	RI	LI	RI	LI	RI	LI	RI	LI
Training	2	3	1	1	1	1	0	0
Enrollment	1	0	2	0	0	0	0	0
Matching Visit 1	0	0	1	0	0	0	0	0
Matching Visit 2	0	0	0	1	0	3	0	0
Matching Visit 3	0	0	0	0	0	1	0	0
Total	3	3	4	2	1	5	0	0

The next analysis combines two similar assist categories, which were “How to use – direction/placement” and “alignment – start position”. The results are shown in Table 95. The results show that the UPEK and PUSH sensor required a higher number of assists than the PULL and LA. However, a continued level of assistance was needed with the UPEK to remind participants where to place their finger and what direction the swipe was to be performed over the DCC, whereas the PUSH and PULL sensors mainly required assistance during visit 1 (training, enrollment, and matching v1). Also, remember that participants had not used the PUSH sensor before this study, but many had used the UPEK. In conclusion, this assist type was likely due to the design of the sensor, as the PUSH and PULL contained visual and tactile cues participants found helpful, whereas the data indicate the UPEK cues may not be helpful.

Table 95 “How to use – direction/placement” and “alignment – start position” combined assist analysis.

	UPEK		PUSH		PULL		LA	
DCC	RI	LI	RI	LI	RI	LI	RI	LI
Training	4	1	4	1	2	0	1	1
Enrollment	3	0	3	1	0	0	0	0
Matching Visit 1	0	0	2	0	0	0	0	0
Matching Visit 2	6	0	0	1	0	0	0	0
Matching Visit 3	3	0	0	0	0	0	3	0
Total	16	1	9	3	2	0	4	1

“Press harder” is the next category and the results are shown in Table 96. The results show that this assistance type was evenly spread across the swipe sensors and DCC. The results indicate that the acquisition problems causing the assist from the author may have been an issue with the acquisition algorithm, rather than the design of the sensor. This claim requires further investigation and data.

Table 96 “Press harder” assist analysis.

	UPEK		PUSH		PULL		LA	
DCC	RI	LI	RI	LI	RI	LI	RI	LI
Training	0	1	2	2	1	2	1	1
Enrollment	4	0	1	0	1	1	0	0
Matching Visit 1	0	0	1	0	0	1	0	0
Matching Visit 2	2	0	1	2	1	4	0	0
Matching Visit 3	1	1	0	0	0	1	0	0
Total	7	2	5	4	3	9	1	1

The next assist type is “Slow down”, which revealed an interesting pattern across the DCCs for the three swipe sensors. Table 97 shows the tabulated results and shows a fair distribution of total assists. However, if we examine the table more closely, the majority of the assists for the PUSH occur in training and enrollment, whereas for the UPEK and PULL they continue over the matching DCCs. This is an interesting and may be due to the different interaction of “pushing” instead of “pulling”.

Table 97 “Slow down” assist analysis.

	UPEK		PUSH		PULL		LA	
DCC	RI	LI	RI	LI	RI	LI	RI	LI
Training	2	2	6	1	4	2	0	0
Enrollment	1	1	3	1	5	1	0	0
Matching Visit 1	1	0	1	0	3	0	0	0
Matching Visit 2	7	0	2	2	6	1	0	0
Matching Visit 3	3	1	2	0	1	0	0	0
Total	14	4	14	4	19	4	0	0

Opposite to slowing down, was the assistance category “faster”, which was only six times throughout the study. The results are shown in Table 98 and reveal the instruction was only given in training or enrollment and was evenly spread across the 3 swipe sensors.

Table 98 “Faster” assist analysis.

	UPEK		PUSH		PULL		LA	
DCC	RI	LI	RI	LI	RI	LI	RI	LI
Training	0	1	1	0	0	1	0	0
Enrollment	1	0	1	0	1	0	0	0
Matching Visit 1	0	0	0	0	0	0	0	0
Matching Visit 2	0	0	0	0	0	0	0	0
Matching Visit 3	0	0	0	0	0	0	0	0
Total	1	1	2	0	1	1	0	0

The last assistance type was “Physical Intervention”, which was only given after the verbal instructions were exhausted. “Physical Intervention” was defined as anytime a participant could not complete the task on his or her own and the author physically intervened and assisted the participant with the presentation to the sensor. The results of this category are shown in Table 99 and reveal a large number occurred during the training DCC with the PUSH sensor. Analyzing the remaining DCC for the PUSH, the number was minimal like the other swipe sensors. The large number during training was likely due to individuals not being used to the motion of the PUSH sensor, as it was different than the UPEK sensor many were accustomed to.

Table 99 “Physical Intervention” assist analysis.

	UPEK		PUSH		PULL		LA	
DCC	RI	LI	RI	LI	RI	LI	RI	LI
Training	1	0	11	1	1	2	0	0
Enrollment	1	0	1	1	0	0	0	0
Matching Visit 1	0	0	0	0	0	0	0	0
Matching Visit 2	0	0	2	2	0	0	0	0
Matching Visit 3	0	0	0	0	0	2	0	0
Total	2	0	14	4	1	4	0	0

4.4.4. Effectiveness

The measurement for effectiveness in this study was the number of errors participants performed while interacting with the four sensors in this study. For biometrics, and especially in this study, the number of errors is directly linked to the Failure to Acquire (FTA) measurement, which will be discussed as a measurement of biometric performance in the next section.

4.5. Biometric Performance

The last component of the HBSI evaluation method (Figure 90) is biometric performance. Technical biometric performance testing seeks to determine error and throughput rates, with the goal of understanding and predicting the real-world error and throughput performance of biometric systems (International Standards Organization, 2006a, p. vi). The biometric system performance component of the evaluation method consisted of multiple metrics, which included Failure to Acquire (FTA), Failure to Enroll (FTE), and Detection Error Tradeoff (DET) curves, which have been broken down by data collection component, sensor, and finger and are discussed in the following sections.

Figure 115 below provides example images from all four sensors tested in this evaluation. Participant 66 did not have many interaction issues or FTAs and provided images of consistent quality, whereas participant 005 had many interaction issues, FTAs, and when acquisition did succeed, poor image quality resulted.

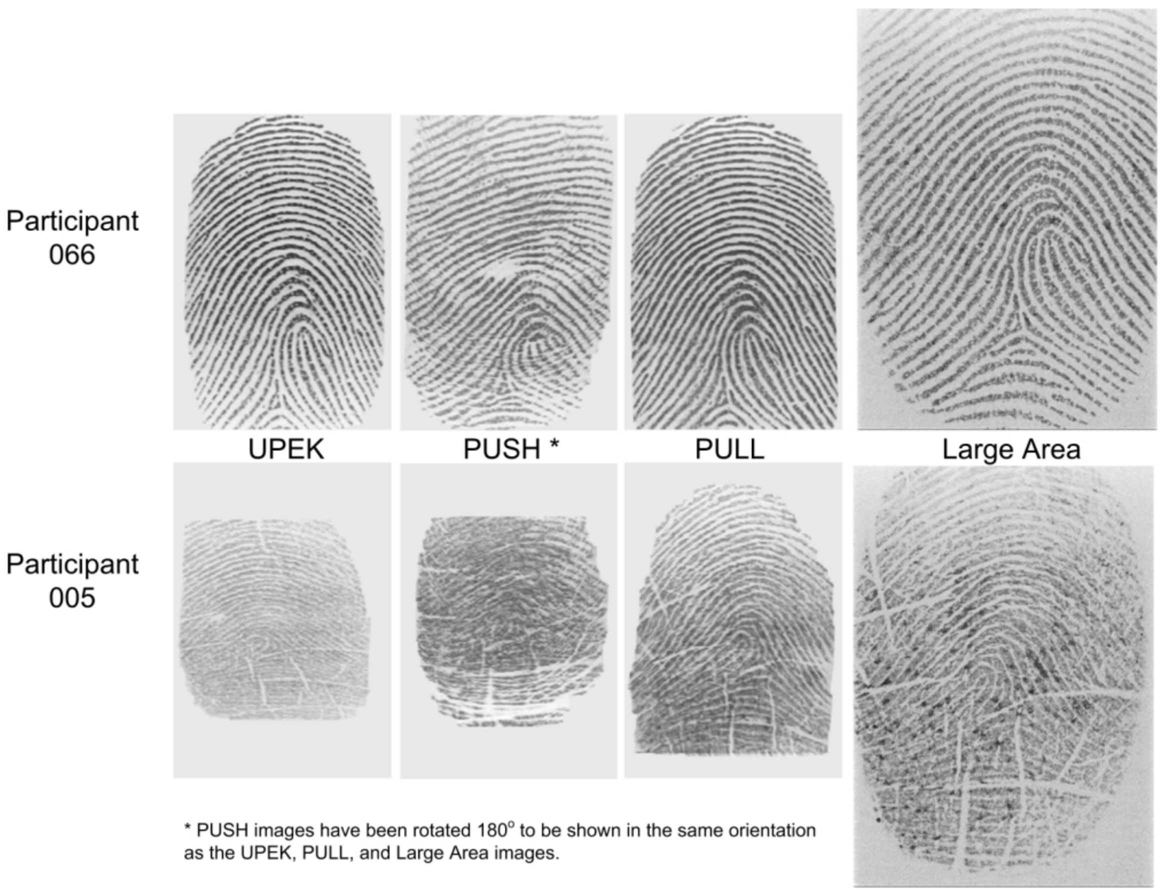


Figure 115 Example fingerprint images from the four sensors used in this study.

4.5.1. Failure to Acquire

The FTA rate was defined in this study as the proportion of verification or identification attempts for which the system failed to capture or locate an image or signal of sufficient quality; which may have included attempts where extracted features were substandard. Table 100 outlines the classification scheme that was used to determine the FTA rates in the categories outlined in NISTIR 7378 (2006) and modified for use in this research. The following six sections discuss the overall FTA rate, and the FTA rates that occurred in each of the five data collection components. The hypothesis that investigates the FTA stated: There is a significant difference in the Failure to Acquire (FTA) rate between the new form factor(s) and the commercially available form factor.

Table 100 HBSI interaction and FTA attempt classification taxonomy used based on NISTIR 7378 (2006).

	Acceptability	
Conformance	**Acceptable Conformant** Interaction/presentation that was performed *correctly* and produced an acceptable fingerprint image.	**Unacceptable Conformant** *Traditional FTA.* An Interaction/presentation that was performed, but was unacceptable to the system, did not produce a fingerprint image, and provided system feedback.
	Acceptable Non-Conformant *False Failure to Present (FFTP).* Interaction/presentation that was performed *incorrectly* but produced an acceptable fingerprint image.	**Unacceptable Non-Conformant** *Failure to Present (FTP).* No presentation and system timeout *or* an interaction/attempt that was performed but was unrecognizable or not detected by the system.

4.5.1.1. Overall

The study consisted of 85 participants that interacted with the four sensors 33,394 times, of which 29,626 (88.72%) were acceptable conformant and 3,768 (11.28%) were classified as acquisition failures. Table 101 provides a breakdown of the overall FTA and acceptable attempts by sensor and finger. In order to compare the results against the commercial UPEK sensor, the Marascuillo procedure for comparing multiple proportions was used. The Marascuillo procedure was deigned to compare the PUSH, PULL, and Large Area sensors to the UPEK sensor. Therefore, all analyses will be reported in this way.

Table 101 Breakdown of acceptable attempts versus combined FTA attempts.

	Acceptable Conformant				FTA Attempts Combined			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	3725	87.92%	3714	87.24%	512	12.08%	543	12.76%
PUSH	3606	83.11%	3653	80.22%	733	16.89%	901	19.78%
PULL	3720	85.71%	3730	90.10%	620	14.29%	410	9.90%
LA	3740	99.52%	3738	99.18%	18	0.48%	31	0.82%
Total	14791	89.06%	14835	89.18%	1883	10.94%	1885	10.82%

Table 102 revealed the overall results of the acceptable conformant attempts versus FTA attempts, which used a significance level (α) of 0.05. 0 extends the overall analysis of the FTA attempts by the HBSI interaction classification taxonomy (Table 100), as well as breaks down the acceptable non-conformant and unacceptable non-conformant by data collection component, sensor, and finger. Interpreting Table 102, the PUSH sensor was significantly worse than the UPEK sensor for both the right and left index fingers. The large area sensor was significantly better than the UPEK sensor for both fingers, which was expected due to the sensor type being a placement sensor. Lastly, the PULL sensor performed significantly better than the UPEK sensor for the right index finger, but exhibited no statistical difference for the interactions with the left index finger.

Table 102 Marascuillo procedure for comparing multiple proportions of Acceptable Conformant and FTA attempts.

	Acceptable Conformant		FTA Attempts Combined	
Sensor	LI	RI	LI	RI
PUSH	$p < .05$	$p < .05$	$p < .05$	$p < .05$
PULL	*n. s.*	$p < .05$	*n. s.*	$p < .05$
LA	$p < .05$	$p < .05$	$p < .05$	$p < .05$

As discussed above, the unacceptable conformant category was an interaction/presentation that was performed, but was unacceptable to the system, did not produce a fingerprint image, and provided system feedback. This definition aligns well with the traditional FTA metric. In this study, the software provided three system feedback messages: “too fast”, “center and press harder”, and “captured and failed”. Before continuing with the FTA analysis, these three feedback messages will be discussed.

The results for “too fast” for the three swipe sensors and five DCCs are shown in Table 103 that reveal the “pull”-based sensors have a significantly larger issue with speed than the “push”-based sensor. The motion the PUSH sensor required for interacting with the sensor was the only difference as the software was the same, indicating the PUSH sensor design may be able to reduce acquisition errors. This will be interesting to investigate in future research.

Table 103 FTA system feedback analysis for “too fast”.

	UPEK		PUSH		PULL	
DCC	RI	LI	RI	LI	RI	LI
Training	14	19	8	2	24	20
Enrollment	46	64	6	9	56	62
Matching Visit 1	50	43	18	21	42	52
Matching Visit 2	46	49	15	8	55	43
Matching Visit 3	43	42	6	15	57	58
Total	199	217	53	55	234	235

“Center & press harder” is the next system feedback the software provided. The results are shown in Table 104. As discussed in previous sections and shown in the fingerprint images, the acquisition algorithm was problematic with the PUSH sensor. The acquisition failures were due this sensor being a prototype device with the algorithm being modified by UPEK for in the research. Thus, the acquisition algorithm was not adjusted to receiving the signal the “push” motion produced, which can be seen with the inflated numbers the PUSH sensor produced. Further FTA analyses will be interesting to study in the future, especially with an acquisition algorithm that is tuned for a “push” motion. In addition, participants had issues with the UPEK and PULL sensors, with the UPEK producing 62 more FTAs than the PULL. In addition to the future work with the PUSH, it would be interesting to further understand why the algorithm is rejecting these presentations.

Table 104 FTA system feedback analysis for “center & press harder”.

	UPEK		PUSH		PULL	
DCC	RI	LI	RI	LI	RI	LI
Training	20	15	102	69	20	42
Enrollment	63	20	145	153	17	29
Matching Visit 1	33	25	111	58	19	31
Matching Visit 2	63	20	97	81	22	28
Matching Visit 3	25	33	67	58	14	33
Total	204	113	522	419	92	163

The last type of feedback the system provided was where the system captured the fingerprint image and displayed a failed message. The results of this FTA feedback type are shown in Table 105. Like the “center & press harder” the “capture and failed“ category is more of an algorithm issue than an interaction issue. Again, the algorithm was adjusted and expecting fingerprint images from a “pull” swipe, therefore negatively weighting the PUSH sensor. However, participants produced a similar number of FTAs with the PUSH sensor outside of the training data collection component. Again it will be interesting in future work to assess system feedback with the PUSH sensor with an algorithm that is adjusted to receive images from a “push”-based sensor.

Table 105 FTA system feedback analysis for “captured and failed”.

	UPEK		PUSH		PULL	
DCC	RI	LI	RI	LI	RI	LI
Training	2	1	10	6	0	1
Enrollment	3	2	3	3	1	5
Matching Visit 1	1	0	4	0	0	3
Matching Visit 2	1	1	3	1	1	3
Matching Visit 3	0	5	1	1	0	2
Total	7	9	21	11	2	14

The next 5 sections investigate the four categories discussed in the HBSI interaction and FTA taxonomy (Table 100) by data collection component.

4.5.1.2. Training

Table 106 provides a breakdown of the results for the training interactions. In order to compare the results against the commercial UPEK sensor, the Marascuillo procedure for comparing multiple proportions was used. Table 107 shows the results of the procedure, which used a significance level (α) of 0.05. Interpreting the table, there were no differences between the UPEK and PULL, meaning statistically they performed similarly, whereas the PUSH performed worse, and the LA performed better than the UPEK for both right and left index fingers.

Table 106 FTA breakdown for training interactions by sensor and finger.

	Acceptable Conformant				Unacceptable Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	340	83.33%	340	84.79%	35	8.58%	36	8.98%
PUSH	330	73.01%	331	66.33%	78	17.26%	120	24.05%
PULL	336	78.32%	340	82.52%	63	14.69%	45	10.92%
LA	340	99.71%	338	97.69%	0	0.00%	0	0.00%

	Acceptable Non-Conformant				Unacceptable Non-Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	0	0.00%	0	0.00%	33	8.09%	25	6.23%
PUSH	0	0.00%	4	0.80%	44	9.73%	44	8.82%
PULL	0	0.00%	2	0.49%	30	6.99%	25	6.07%
LA	1	0.29%	2	0.58%	0	0.00%	6	1.73%

Table 107 Marascuillo procedure for comparing multiple proportions for the training interactions.

	Acceptable Conformant		Unacceptable Conformant	
Sensor	LI	RI	LI	RI
PUSH	$p < .05$	$p < .05$	$p < .05$	$p < .05$
PULL	*n. s.*	*n. s.*	*n. s.*	*n. s.*
LA	$p < .05$	$p < .05$	$p < .05$	$p < .05$

	Acceptable Non-Conformant		Unacceptable Non-Conformant	
Sensor	LI	RI	LI	RI
PUSH	*n. s.*	*n. s.*	*n. s.*	*n. s.*
PULL	*n. s.*	*n. s.*	*n. s.*	*n. s.*
LA	*n. s.*	*n. s.*	$p < .05$	$p < .05$

4.5.1.3. Enrollment

Table 108 provides a breakdown of the results for the enrollment interactions. In order to compare the results against the commercial UPEK sensor, the Marascuillo procedure for comparing multiple proportions was used. Table 109 shows the results of the procedure, which used a significance level (α) of 0.05. Interpreting the table, there were no differences between the UPEK and PULL for the left index finger, however the PULL sensor performed better for the right index. Like the training results, the PUSH performed worse, and the LA performed better than the UPEK for both right and left index fingers.

Table 108 FTA breakdown for enrollment interactions by sensor and finger.

	Acceptable Conformant				Unacceptable Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	850	88.08%	845	84.08%	86	8.91%	112	11.14%
PUSH	827	78.39%	832	77.54%	165	15.64%	154	14.35%
PULL	850	85.95%	850	90.14%	96	9.71%	74	7.85%
LA	850	99.53%	850	99.88%	0	0.00%	0	0.00%

	Acceptable Non-Conformant				Unacceptable Non-Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	0	0.00%	0	0.00%	29	3.01%	48	4.78%
PUSH	0	0.00%	0	0.00%	63	5.97%	87	8.11%
PULL	0	0.00%	0	0.00%	43	4.35%	19	2.01%
LA	0	0.00%	0	0.00%	4	0.47%	1	0.12%

Table 109 Marascuillo procedure for comparing multiple proportions for the enrollment interactions.

	Acceptable Conformant		Unacceptable Conformant	
Sensor	LI	RI	LI	RI
PUSH	$p < .05$	$p < .05$	$p < .05$	*n. s.*
PULL	*n. s.*	$p < .05$	*n. s.*	*n. s.*
LA	$p < .05$	$p < .05$	$p < .05$	$p < .05$

	Acceptable Non-Conformant		Unacceptable Non-Conformant	
Sensor	LI	RI	LI	RI
PUSH	-	-	$p < .05$	$p < .05$
PULL	-	-	*n. s.*	$p < .05$
LA	-	-	$p < .05$	$p < .05$

4.5.1.4. Matching Visit 1

Table 110 provides a breakdown of the results for the matching visit 1 interactions. In order to compare the results against the commercial UPEK sensor, the Marascuillo procedure for comparing multiple proportions was used. Table 111 shows the results of the procedure, which used a significance level (α)

of 0.05. Interpreting the table, there were no differences between both fingers of the UPEK and PULL, as well as the left index interactions on the PUSH. Investigating the results of the Marascuillo procedure further for the UPEK and PULL, a difference in p-values of 0.001 was the difference between detecting a statistical difference based on the critical value and significance level.

Table 110 FTA breakdown for matching visit 1 interactions sensor and finger.

	Acceptable Conformant				Unacceptable Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	850	89.19%	850	88.82%	68	7.14%	80	8.36%
PUSH	820	87.33%	829	81.76%	79	8.41%	133	13.12%
PULL	849	86.90%	850	92.39%	86	8.80%	61	6.63%
LA	850	99.77%	850	99.53%	0	0.00%	0	0.00%

	Acceptable Non-Conformant				Unacceptable Non-Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	0	0.00%	0	0.00%	35	3.67%	27	2.82%
PUSH	0	0.00%	2	0.20%	40	4.26%	50	4.93%
PULL	0	0.00%	0	0.00%	42	4.30%	9	0.98%
LA	1	0.12%	0	0.00%	1	0.12%	4	0.47%

Table 111 Marascuillo procedure for comparing multiple proportions for the matching visit 1 interactions.

	Acceptable Conformant		Unacceptable Conformant	
Sensor	LI	RI	LI	RI
PUSH	*n. s.*	$p < .05$	*n. s.*	$p < .05$
PULL	*n. s.*	*n. s.*	*n. s.*	*n. s.*
LA	$p < .05$	$p < .05$	$p < .05$	$p < .05$

	Acceptable Non-Conformant		Unacceptable Non-Conformant	
Sensor	LI	RI	LI	RI
PUSH	*n. s.*	*n. s.*	*n. s.*	*n. s.*
PULL	*n. s.*	*n. s.*	*n. s.*	*n. s.*
LA	*n. s.*	*n. s.*	$p < .05$	$p < .05$

4.5.1.5. Matching Visit 2

Table 112 provides a breakdown of the results for the matching visit 2 interactions. In order to compare the results against the commercial UPEK sensor, the Marascuillo procedure for comparing multiple proportions was used. Table 113 shows the results of the procedure, which used a significance level (α) of 0.05. Interpreting the table, there were no differences between the UPEK, PUSH, and PULL, meaning statistically they performed similarly.

Table 112 FTA breakdown for matching visit 2 interactions by sensor and finger.

	Acceptable Conformant				Unacceptable Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	836	88.19%	839	86.76%	70	7.38%	110	11.38%
PUSH	810	85.26%	830	82.83%	90	9.47%	115	11.48%
PULL	838	87.11%	840	90.13%	74	7.69%	78	8.37%
LA	850	99.18%	850	99.18%	0	0.00%	0	0.00%

	Acceptable Non-Conformant				Unacceptable Non-Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	0	0.00%	0	0.00%	42	4.43%	18	1.86%
PUSH	1	0.11%	0	0.00%	49	5.16%	57	5.69%
PULL	0	0.00%	0	0.00%	50	5.20%	14	1.50%
LA	0	0.00%	0	0.00%	7	0.82%	7	0.82%

Table 113 Marascuillo procedure for comparing multiple proportions for the matching visit 2 interactions.

	Acceptable Conformant		Unacceptable Conformant	
Sensor	LI	RI	LI	RI
PUSH	*n. s.*	*n. s.*	*n. s.*	*n. s.*
PULL	*n. s.*	*n. s.*	*n. s.*	*n. s.*
LA	$p < .05$	$p < .05$	$p < .05$	$p < .05$

	Acceptable Non-Conformant		Unacceptable Non-Conformant	
Sensor	LI	RI	LI	RI
PUSH	*n. s.*	-	*n. s.*	$p < .05$
PULL	*n. s.*	-	*n. s.*	*n. s.*
LA	*n. s.*	-	$p < .05$	*n. s.*

4.5.1.6. Matching Visit 3

Table 114 provides a breakdown of the results for the matching visit 3 interactions. In order to compare the results against the commercial UPEK sensor, the Marascuillo procedure for comparing multiple proportions was used. Table 115 shows the results of the procedure, which used a significance level (α) of 0.05. Interpreting the table, there were no differences between both fingers of the UPEK and PULL, as well as the left index interactions on the PUSH, meaning statistically they performed similarly. Table 114 provides additional details on the feedback the system delivered for the unacceptable conformant interaction attempts.

Table 114 FTA breakdown for matching visit 3 interactions by sensor and finger.

	Acceptable Conformant				Unacceptable Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	849	88.16%	840	90.61%	80	8.31%	68	7.34%
PUSH	819	86.85%	831	86.02%	74	7.85%	74	7.66%
PULL	847	86.16%	850	91.10%	93	9.46%	71	7.61%
LA	850	99.53%	850	98.72%	0	0.00%	0	0.00%

	Acceptable Non-Conformant				Unacceptable Non-Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	0	0.00%	0	0.00%	34	3.53%	19	2.05%
PUSH	0	0.00%	0	0.00%	50	5.30%	61	6.31%
PULL	0	0.00%	0	0.00%	43	4.37%	12	1.29%
LA	0	0.00%	0	0.00%	4	0.47%	11	1.28%

Table 115 Marascuillo procedure for comparing multiple proportions for the matching visit 3 interactions.

	Acceptable Conformant		Unacceptable Conformant	
Sensor	LI	RI	LI	RI
PUSH	*n. s.*	$p < .05$	*n. s.*	*n. s.*
PULL	*n. s.*	*n. s.*	*n. s.*	*n. s.*
LA	$p < .05$	$p < .05$	$p < .05$	$p < .05$

	Acceptable Non-Conformant		Unacceptable Non-Conformant	
Sensor	LI	RI	LI	RI
PUSH	-	-	*n. s.*	$p < .05$
PULL	-	-	*n. s.*	*n. s.*
LA	-	-	$p < .05$	*n. s.*

4.5.1.7. Hypothesis Testing Summary: Failure to Acquire

The Failure to Acquire (FTA) was evaluated using the Chi-square (χ^2) test and Marascuillo procedure in order to compare the results of the different form factors with the hypothesis that there is a significant difference in the FTA rate of the new form factor(s) and the commercially available form factor.

The results of the study revealed that there was a statistically significant difference between the large area and the UPEK sensor, indicating that swipe-based sensors continue to need improvement. Table 116 shows a summary table of the FTA rates by sensor and finger. The results show that there is no difference between the PULL and UPEK with the left index finger, but the PULL sensor had a significantly lower FTA rate with the right index finger. While the PUSH sensor had a higher FTA rate than the UPEK sensor with both fingers, the FTA rate could have been due to the acquisition algorithm being tuned to “pull”-based images and not solely the result of interaction issues. This will be of extreme interest to work with UPEK in developing a “push”-based acquisition algorithm to reappraise the performance and functionality of the PUSH sensor.

Table 116 Summary FTA table with statistical results.

	Left Index Finger		Right Index Finger	
Sensor	Statistical test	FTA %	Statistical test	FTA %
UPEK	-	12.08%	-	12.76%
PUSH	$p < .05$	16.89%	$p < .05$	19.78%
PULL	*n. s.*	14.29%	$p < .05$	9.90%
LA	$p < .05$	0.48%	$p < .05$	0.82%

4.5.2. Failure to Enroll

The Failure to Enroll (FTE) rate was defined in this study as the proportion of the population that the biometric system fails to complete the enrollment process. The hypothesis that investigated the FTE rate was stated as: There is a significant difference in the Failure to Enroll (FTE) rate of the new form factor(s) and the commercially available form factor. The FTE in this study consisted of two measures: the acquisition level FTE and algorithm level extraction FTE.

4.5.2.1. Acquisition level FTE

The acquisition level FTE was defined as enrollment attempts that failed to produce 10 fingerprint images with the constraint of 30 consecutive presentations. Of the 85 participants, only 6 FTEs were registered in a possible 680 enrollments (85 participants x 4 sensors x 2 fingers). The FTEs are classified by sensor and finger in Table 117. Since only 6 acquisition level FTEs occurred, the statistical test was unnecessary. It was interesting to note that the PULL sensor produced no acquisition level FTEs.

Table 117 Acquisition level FTE by sensor and finger.

Sensor	Finger	N	Acquisition FTE rate
UPEK	RI	1	1.18%
PUSH	RI	2	2.35%
PUSH	LI	3	3.53%

4.5.2.2. Algorithm level extraction FTE

An extraction level FTE was defined in this study as an image that failed to meet the criteria of the algorithm used for feature extraction. This rate was computed once all the fingerprint data were collected, during the offline analysis. Fingerprint feature extraction and matching was performed using the Neurotechnologija VeriFinger 5.0 algorithm. The enrollment parameters were set to default; a minimum of 10 minutiae had to be present, as well as the quality threshold exceeding the 39% value. Table 118 shows the overall extraction level FTE, which is further broken down by data collection component in Table 119. To test for differences in the extraction level FTE rates against the UPEK sensor, the Marascuillo procedure for comparing multiple proportions, using a significance level (α) of 0.05 was used. Overall, the PUSH and PULL sensors had higher extraction level FTE rates that were statistically significant, whereas there were no differences between the UPEK and LA (Table 120). The Marascuillo procedure was also used to investigate differences in the four sensors across the five data collection components, which only indicated differences in the PUSH training and matching visit 3 data collection components.

Table 118 Overall extraction level FTE rate and number of images by sensor.

	Total Extraction FTE Rate	
Sensor	N	%
UPEK	179	2.41%
PUSH	295	4.09%
PULL	248	3.32%
LA	160	2.14%

Table 119 Extraction level FTE rate and number of images by sensor and data collection component.

	Data collection component									
	Training		Enrollment		Matching V1		Matching V2		Matching V3	
Sensor	N	%	N	%	N	%	N	%	N	%
UPEK	10	1.47%	40	2.37%	50	2.96%	45	2.68%	34	2.01%
PUSH	35	5.15%	57	3.50%	80	4.89%	57	3.50%	66	4.03%
PULL	21	3.11%	60	3.51%	48	2.82%	57	3.40%	62	3.65%
LA	11	1.62%	24	1.41%	41	2.41%	52	3.06%	32	1.88%

Table 120 Marascuillo procedure for comparing multiple proportions for the extraction level FTE.

	Sensor compared to UPEK		
Data collection component	PUSH	PULL	LA
Training	$p < .05$	*n.s.*	*n.s.*
Enrollment	*n.s.*	*n.s.*	*n.s.*
Matching V1	*n.s.*	*n.s.*	*n.s.*
Matching V2	*n.s.*	*n.s.*	*n.s.*
Matching V3	$p < .05$	*n.s.*	*n.s.*
OVERALL	$p < .05$	$p < .05$	*n.s.*

4.5.3. Matching Performance

Fingerprint matching was performed offline using the Neurotechnologija VeriFinger 5.0 algorithm, which is a minutiae-based matcher. To analyze matching performance, Detection Error Trade-off (DET) curves were used, which plot the false acceptance rate versus the false rejection rate. According to Clark & Clark (2005), “DET curves usually utilize logarithmic scales on both axes”, which “tend to be more spread out than ROC curves, making it easier to distinguish individual algorithm’s results” (p. 8). Overlaid on each DET curve is the equal error rate (EER), which is the point where False Accept Rate (FAR) and False Reject Rate (FRR) intersect, making it easier to compare the results for each sensor and finger. The lower the EER, the better the performance. DET curves were created for each sensor and finger dataset in each of the five data collection components.

For this document, DET curves for each data collection component, sensor, and finger were created, which can be found in Appendix CC. From these DETs Table 121 was populated, which shows the reported FRR at the operational point of 0.1 FAR, which was chosen arbitrarily for comparison purposes. In addition to the DETs by data collection component, Appendix DD contains the DETs by sensor, showing how performance changed over the DCCs by sensor.

Table 121 Reported FRR at 0.1% FAR by sensor, index finger, and data collection component.

	Left Index FRR at 0.1% FAR					
Sensor	Training	Enrollment	Match V1	Match V2	Match V3	Mean FRR
UPEK	0.00%	0.10%	0.35%	0.60%	0.50%	0.31%
PUSH	0.20%	1.10%	0.80%	0.80%	0.60%	0.70%
PULL	0.20%	0.20%	0.35%	0.10%	1.20%	0.41%
LA	0.20%	0.10%	0.40%	0.35%	0.50%	0.31%

	Right Index FRR at 0.1% FAR					
Sensor	Training	Enrollment	Match V1	Match V2	Match V3	Mean FRR
UPEK	0.00%	0.15%	0.10%	0.45%	0.10%	0.16%
PUSH	2.00%	1.50%	1.00%	0.60%	1.20%	1.26%
PULL	0.20%	0.00%	0.50%	0.60%	0.21%	0.30%
LA	0.80%	0.30%	0.30%	0.35%	0.10%	0.37%

Analyzing the table, the reported FRR did not vary significantly over the course of the study and did not surpass 2% for any of the sensors. Overall, the average FRR was 0.52% at 0.1% FAR for all sensors, fingers, and DCCs. Examining the data by sensor, the PUSH performed the worst for both fingers, which as discussed in earlier sections, was likely due to the prototype device and acquisition algorithm being adjusted for “pull”-based fingerprint images. Moreover, the average FRR for the PUSH was less than 1.3% for both fingers at 0.1% FAR. The best performing sensor in this study was the UPEK sensor for both fingers, although the LA left index finger tied at 0.31% FRR. It was interesting to observe the LA had slightly lower performance numbers than the swipe sensors, although recall the AIMQ scores were lower for the large area, which image quality is correlated with matching performance. Yet, both fingers had a FRR that was less than 0.37%. Lastly, the PULL sensor performed similarly to the UPEK and LA sensors, with left and right index finger FRRs of 0.41% and 0.30%, respectively.

4.6. Summary HBSI Evaluation Method Results

The HBSI evaluation method (Figure 48) outlined six areas for evaluating the four fingerprint form factors, which statistical methods were outlined in Table 13. The following 7 tables present the results from the study according to the HBSI evaluation method metrics. The summary reports the following results:

1. Table 122 Statistical test results for the HBSI evaluation method metrics for ergonomics / image quality.
2. Table 123 Test results for the HBSI evaluation method metrics for usability results for learnability.
3. Efficiency can be found in Table 88.

4. Table 124 Statistical significance summary results for the HBSI evaluation method metrics for effectiveness/ overall FTA.
5. Table 125 Statistical significance results for the HBSI evaluation method metrics for effectiveness/FTA by HBSI classification taxonomy.
6. Table 126 Results of the HBSI evaluation method metrics for biometric performance: Acquisition level FTE.
7. Table 127 Results of the HBSI evaluation method metrics for biometric performance: Extraction level FTE.
8. Table 128 Results of the HBSI evaluation method metrics for biometric performance: Matching performance.

Table 122 Statistical test results for the HBSI evaluation method metrics for ergonomics / image quality.

HBSI Evaluation Method Metrics for: Ergonomics / Image Quality	Data Collection Component (DCC)	*p*-value Finger	*p*-value Sensor	*p*-value Finger* Sensor	Post Hoc Analysis Tukey Pairwise Comparison	Result Sensor Hypothesis Test (α = 0.05)
Aware Image Quality (AIMQ)	Training	0.000	0.000	0.727	UPEK = PULL	Accept
	Enrollment	0.000	0.000	0.751	UPEK = PULL	Accept
	Matching V1	0.000	0.000	0.002	All pairwise differences significant	Accept
	Matching V2	0.000	0.000	0.051	UPEK = PULL	Accept
	Matching V3	0.000	0.000	0.068	All pairwise differences significant	Accept
Number of Detected Minutiae	Training	0.003	0.000	0.876	UPEK = PULL	Accept
	Enrollment	0.000	0.000	0.695	UPEK = PULL	Accept
	Matching V1	0.000	0.000	0.016	All pairwise differences significant	Accept
	Matching V2	0.003	0.000	0.055	All pairwise differences significant	Accept
	Matching V3	0.003	0.000	0.042	UPEK = PULL	Accept
Image Size / Area	Training	0.344	0.000	0.349	UPEK = PULL	Accept
	Enrollment	0.991	0.000	0.000	UPEK = PULL	Accept
	Matching V1	0.83	0.000	0.000	UPEK = PULL	Accept
	Matching V2	0.167	0.000	0.002	All pairwise differences significant	Accept
	Matching V3	0.083	0.000	0.000	All pairwise differences significant	Accept
Image Contrast	Training	0.001	0.000	0.562	All pairwise differences significant	Accept
	Enrollment	0.000	0.000	0.163	All pairwise differences significant	Accept
	Matching V1	0.035	0.000	0.689	UPEK = PULL	Accept
	Matching V2	0.001	0.000	0.561	UPEK = PULL	Accept
	Matching V3	0.895	0.000	0.289	UPEK = PULL	Accept

Table 123 Test results for the HBSI evaluation method metrics for usability results for learnability.

HBSI Evaluation Method Metric for: Learnability	Sensor	Left Index	Right Index	Overall Rate, Average, (StDev)
Task Completion	UPEK	99.28%	98.80%	99.10%
	PUSH	96.00%	97.14%	96.60%
	PULL	98.80%	99.76%	99.30%
	LA	100.00%	100.00%	100%
Maximum User Effort*	UPEK	11.26 (2.31)	11.35 (2.63)	11.30 (2.47)
	PUSH	11.43 (3.92)	11.92 (4.01)	11.67 (3.95)
	PULL	11.50 (2.91)	10.96 (1.88)	11.23 (2.39)
	LA	10.05 (0.27)	10.10 (0.31)	10.07 (0.29)
Assists	UPEK	6.10%	22.80%	28.90%
	PUSH	9.60%	31.50%	41.10%
	PULL	12.70%	13.70%	26.40%
	LA	1.00%	2.50%	3.50%

* Only includes mean of Enrollment, Matching Visit 1, 2, and 3.

Table 124 Statistical significance summary results for the HBSI evaluation method metrics for effectiveness/ overall FTA.

HBSI Evaluation Method Metric for: Effectiveness/ Biometric Performance	Sensor	Left Index Finger		Right Index Finger	
		Statistical test	FTA %	Statistical test	FTA %
Overall FTA	UPEK	-	12.08%	-	12.76%
	PUSH	Yes	16.89%	Yes	19.78%
	PULL	No	14.29%	Yes	9.90%
	LA	Yes	0.48%	Yes	0.82%

Table 125 Statistical significance results for the HBSI evaluation method metrics for effectiveness/FTA by HBSI classification taxonomy.

HBSI Evaluation Method Metric for: Effectiveness/ Biometric Performance	Data collection component	Class	Marascuillo Statistical Test PUSH LI	PUSH RI	PULL LI	PULL RI	LA LI	LA RI
FTA	Training	AC	Yes	Yes	No	No	Yes	Yes
		UC	Yes	Yes	No	No	Yes	Yes
		ANC	No	No	No	No	No	No
		UNC	No	No	No	No	Yes	Yes
	Enrollment	AC	Yes	Yes	No	Yes	Yes	Yes
		UC	Yes	No	No	No	Yes	Yes
		ANC	-	-	-	-	-	-
		UNC	Yes	Yes	No	Yes	Yes	Yes
	Matching V1	AC	No	Yes	No	No	Yes	Yes
		UC	No	Yes	No	No	Yes	Yes
		ANC	No	No	No	No	No	No
		UNC	No	No	No	No	Yes	Yes
	Matching V2	AC	No	No	No	No	Yes	Yes
		UC	No	No	No	No	Yes	Yes
		ANC	No	-	No	-	No	-
		UNC	No	Yes	No	No	Yes	No
	Matching V3	AC	No	Yes	No	No	Yes	Yes
		UC	No	No	No	No	Yes	Yes
		ANC	-	-	-	-	-	-
		UNC	No	Yes	No	No	Yes	No

AC = Acceptable Conformant, UC = Unacceptable Conformant,
ANC = Acceptable Non-Conformant, UNC = Unacceptable Non-Conformant

Table 126 Results of the HBSI evaluation method metrics for biometric performance: Acquisition level FTE.

HBSI Evaluation Method Metric for: Biometric Performance	Sensor	Finger	N	FTE
Acquisition FTE	UPEK	RI	1	1.18%
	PUSH	RI	2	2.35%
	PUSH	LI	3	3.53%

Table 127 Results of the HBSI evaluation method metrics for biometric performance: Extraction level FTE.

HBSI Evaluation Method Metric for: Biometric Performance		UPEK		PUSH		PULL		LA	
		Test Statistic	FTE	Test Statistic	FTE	Test Statistic	FTE	Test Statistic	FTE
Extraction FTE	Training	-	1.47%	Yes	5.15%	No	3.11%	No	1.62%
	Enrollment	-	2.37%	No	3.50%	No	3.51%	No	1.41%
	Matching V1	-	2.96%	No	4.89%	No	2.82%	No	2.41%
	Matching V2	-	2.68%	No	3.50%	No	3.40%	No	3.06%
	Matching V3	-	2.01%	Yes	4.03%	No	3.65%	No	1.88%

Table 128 Results of the HBSI evaluation method metrics for biometric performance: Matching performance.

HBSI Evaluation Method Metric for: Biometric Performance	Sensor	Left Index FRR at 0.1% FAR					
		Training	Enrollment	Matching V1	Matching V2	Matching V3	Mean FRR
Matching Performance	UPEK	0.00%	0.10%	0.35%	0.60%	0.50%	0.31%
	PUSH	0.20%	1.10%	0.80%	0.80%	0.60%	0.70%
	PULL	0.20%	0.20%	0.35%	0.10%	1.20%	0.41%
	LA	0.20%	0.10%	0.40%	0.35%	0.50%	0.31%
		Right Index FRR at 0.1% FAR					
	Sensor	Training	Enrollment	Matching V1	Matching V2	Matching V3	Mean FRR
	UPEK	0.00%	0.15%	0.10%	0.45%	0.10%	0.16%
	PUSH	2.00%	1.50%	1.00%	0.60%	1.20%	1.26%
	PULL	0.20%	0.00%	0.50%	0.60%	0.21%	0.30%
	LA	0.80%	0.30%	0.30%	0.35%	0.10%	0.37%

CHAPTER 5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

This research confronted two sizeable topics in biometrics that undermine the continued use and adoption of biometric technologies. This section will first describe the two areas investigated, then will discuss the key findings.

The first topic this research examined was if traditional testing and performance evaluation metrics such as FTA, FTE, FAR, and FRR used in the three standardized evaluation methods (technology, scenario, and operational) were sufficient to fully test and understand biometric systems, or determine if important data were not being collected. To do this the Human-Biometric Sensor Interaction conceptual model (Figure 116) and evaluation method (Figure 117) were developed.

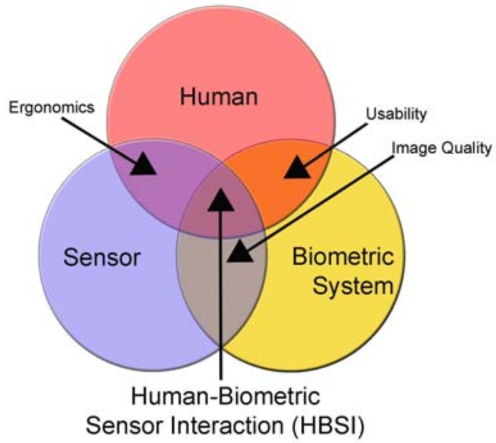


Figure 116 The Human-Biometric Sensor Interaction (HBSI) conceptual model (Elliott, Kukula, & Modi, 2007; Kukula, 2007; Kukula, Elliott, & Duffy, 2007).

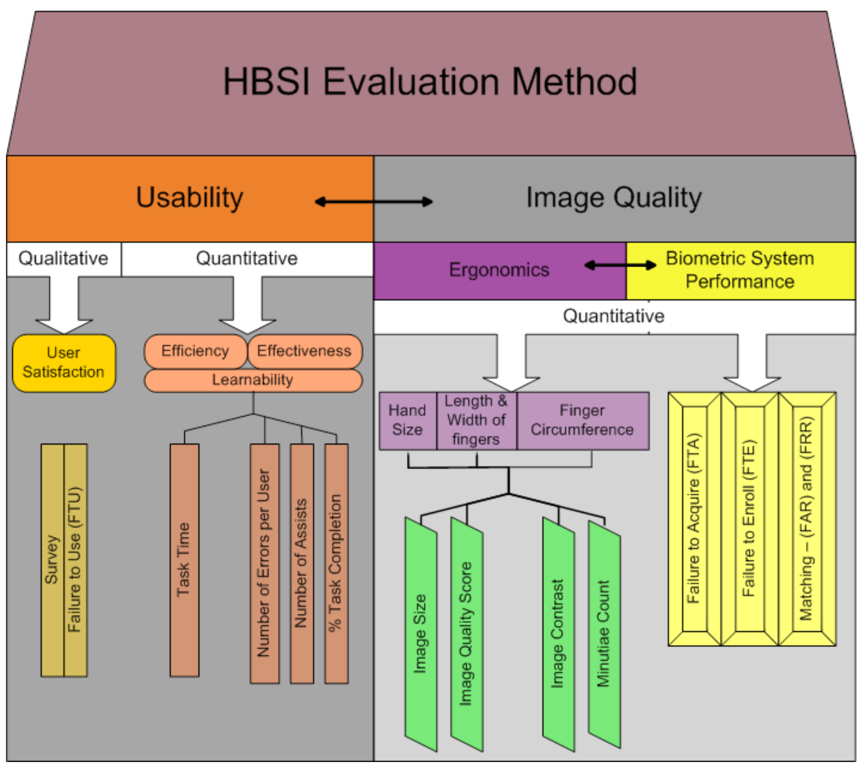


Figure 117 The HBSI evaluation method (Kukula, 2007; Kukula, Elliott, & Duffy, 2007).

The second topic investigated in this research used the HBSI evaluation method to assess swipe-based fingerprint sensors, which previous research by the author revealed acquisition and interaction inconsistencies that warranted further investigation (Kukula & Elliott, 2006; Kukula, Elliott, Wolleschensky, Parsons, & Whitaker, 2007). Therefore, to address this topic, data were collected from interviews, ergonomic literature was referenced, and two swipe-based fingerprint form factors were created and named the PUSH and PULL, originating from the motion required for interaction. The two form factors were then subjected to a comparative evaluation against a commercial swipe-based sensor.

Beginning with traditional biometric testing and reporting analyses, the results from this research revealed the matching performance reported for the UPEK, PUSH, PULL, and large area sensors was relatively acceptable at the 0.1% FAR operational point. However, as the results of this research revealed, significant issues remain, particularly with the presentation and acquisition of the biometric characteristics to the sensor. Prior to this research, the FTA would only have been reported, which was 11.28% overall. However, through the FTA attempt classification taxonomy, two new metrics previously unaccounted for in the three standardized testing and performance evaluation methods, accounted for about 32% of the traditional FTA rate. The two new metrics developed out of the measures of effectiveness and biometric performance were the Failure to Present (FTP) and the False Failure to Present (FFTP) rates.

The FTP consisted of 1,187 of the 3,768 FTA presentations, which accounted for 31.5% of the overall FTA rate. The FTP rate should be of extreme importance to correct and understand as biometric technologies become more pervasive and competing technologies develop. If for example, the FTP rate is not addressed, users may look to other emerging technologies. This illuminates a conundrum; users cannot successfully interact with a biometric device, yet algorithm developers believe there are few problems or issues with their device or algorithm, as biometric testing and evaluations following the technology, scenario, and operational testing standards have reported systems receiving acceptable performance rates.

In addition to the FTP, the False Failure to Present (FFTP) metric was also hidden within the traditional FTA rate. While the FFTP rate was only 0.35%, it is of interest to the biometric community, as it may help explain abnormal behaviors in matching rates or ROC and DET curves.

Removing the FTP and FFTP, the number of traditional FTA presentations was 2,568, which consisted of 68.15% of the original overall FTA rate of 11.28%, which is still significantly high. The HBSI evaluation method can further investigate the FTA and potentially understand these issues even more. This is possible because of the explanatory power of the data collection and analyses protocols, as the biometric system feedback of the FTA presentation was captured in streaming video along with video footage of the users interacting with the sensors that caused the acquisition failure. This linkage could enable algorithm developers and researchers the ability to re-examine the data to see if the FTA is in fact an algorithm issue, or an interaction issue that can be solved by continued training, modifications to the design of the form factor, or some further adjustment.

The assessment of the HBSI evaluation method metrics for ergonomics and image quality revealed that the four metrics used: image quality, number of detected minutiae, fingerprint image area, and fingerprint image contrast provided additional explanatory power than previous biometric testing and evaluations had reported. Previous research used only image quality and number of detected minutiae metrics, whereas this research wanted to further understand how users interact with the sensors.

Examining the additional metrics of fingerprint image area and contrast for the swipe sensors created in this study revealed that the PULL sensor design allowed for images of a larger area to be acquired once individuals became acclimated and habituated to the device (matching visits 2 and 3). Furthermore, the PUSH sensor design allowed users to interact with the sensor to provide the most consistent images in terms of variability of gray levels (image contrast) for all visits in the study, outperforming both “pull”-based sensors. This is an extremely interesting finding given the challenge found during this study of the acquisition algorithm being tuned for images from “pull”-based sensors. The fact the PUSH sensor provided images of the most consistent image contrast provides merit to future work with “push”-type sensors, especially with an acquisition algorithm that is adjusted for acquiring images from a “push” type interaction.

One can further see the acquisition algorithm issue through an investigation of the results for Aware Image Quality and the number of detected minutiae. Both metrics revealed that the PUSH sensor captured the worst quality images and least number of minutiae compared to the UPEK and PULL sensors. With regards to the PULL design, it captured images of relatively similar quality, reported no statistically significant differences in some DCCs, and slightly lower mean results for both quality and minutiae in others.

The usability component of the HBSI evaluation method also provided extremely important data for the biometric testing and evaluation community. First, it provided metrics for efficiency in terms of task time, which was the time for the participant to complete the defined number of presentations to the sensor. With regards to the comparative evaluation, this metric revealed that as participants became more familiar with the PUSH sensor, individuals became more efficient as task times varied widely. Specifically, the standard deviation for the PUSH task time reduced 50% between matching visit 1 and matching visit 3. The task time data provided one of the first biometric evaluations that reported the human-sensor interaction task time as opposed to a biometric sub-system generated timing metric. Therefore, the efficiency metric may lead to a better understanding of acclimation and habituation with biometric devices, although further research is needed to validate this claim. This research would provide the practitioner extremely valuable information regarding throughput times.

Like the measure for efficiency, the metrics for learnability: task completion, assistance, and maximum user effort all provided useful data regarding how users learn to use biometric systems over time.

The number of assists metric was useful in diagnosing the interaction problems participants had, as well as potential issues in the design of the sensors that could be solved if iterative testing was chosen. The results from the comparative evaluation revealed that the PUSH sensor required the most assistance, followed by the UPEK, PULL, and Large Area sensors. The most surprising results from this research was the level of assistance the UPEK required, considering a large number of participants had used the sensor prior to this study.

The task completion and maximum user effort (MUE) metrics were useful in understanding how much effort it too individuals to complete the defined task in this study, and if they were able to complete it in general. Therefore, the task completion rate and MUE should be reported as a separate metric, as they have direct influence on training, throughput, and user acceptance.

In addition to the quantitative metrics of usability, the user satisfaction questionnaire provided a valuable source of information to further understand the HBSI. However, caution must be used when introducing survey instruments with populations that have previous exposure with the biometric devices being evaluated, as these participants could compromise the validity of the tool. Taking the demographics and prior usage of the UPEK sensor into account, the HBSI PSSUQ questionnaire provided data regarding system usefulness, information quality, and interface quality, as well as the overall satisfaction with each of the swipe-based sensors under test, which is the first evaluation of its kind with biometrics.

In summary, this document proposed a new biometric testing and evaluation method that focused on the human interaction with biometric sensors. Additionally, the document discussed the design and comparative evaluation of the PUSH and PULL sensors, created by the author, to the commercial swipe-based sensor. The goal of introducing the HBSI evaluation method was to illuminate problems and interaction issues that traditional biometric technology assessments have previously overlooked in order to assist in the development of improved biometric systems. After careful analysis of the data collected using the HBSI evaluation method proposed in this document, the author is convinced the Human-Biometric Sensor Interaction Evaluation Method provides useful information the biometrics community is in search of to continue improving biometric systems as a whole. With regards to the two sensors created, the visual and tactile cues of the PULL sensor showed improvements in a number of the HBSI evaluation metrics. Additionally, the PUSH sensor should be further investigated, as the data collected in this research reported improvements in key areas of the HBSI.

5.2. Recommendations

Throughout the scope of work in the Design and Evaluation of the Human-Biometric Sensor Interaction Method, future research possibilities emerged from the literature and from the results of this study. The following recommendations for future work in the area of the HBSI are discussed in terms of scope: short term, medium term, and long term.

5.2.1. Short Term

1. Validation and revisions to the HBSI evaluation method. First and foremost, the HBSI evaluation method needs to be revised based upon the results of this study. First, the three quantitative usability silos: efficiency, effectiveness, and learnability should be grouped side by side with the appropriate metrics reported below each silo. Second, the FTA metric under biometric performance should be realigned under usability, specifically the effectiveness silo. This takes into account the HBSI interaction and FTA attempt classification and the two new metrics; FTP and FFTP. Lastly, the commercial image quality metric should be relocated to a new area as the algorithm is a “black box” and limited information is known as to what components of quality it is measuring.
2. Examine the correlation of the image quality metrics proposed in the HBSI evaluation method with matching performance; specifically fingerprint image area and fingerprint image contrast.
3. Work with UPEK, Inc on the acquisition algorithm for the “push”-based swipe device in order to be able to better understand the potential of using a “push” versus “pull” swipe fingerprint sensor using algorithms that are tuned for the appropriate interaction type.

4. Define Failure to Present (FTP) and False Failure to Present (FFTP) to the biometrics community. The results of this study based on the HBSI FTA analysis and the FTA attempt classification taxonomy produced two metrics that provide valuable information to the biometrics community in terms of a more formal method to evaluate the usability of biometric systems. This may include a submission to INCITS M1 and/or ISO/IEC JTC1 SC37 Testing and Reporting technical experts, as well as Vocabulary experts.

5.2.2. Medium Term

1. Replication of this study using the “push” and “pull” based swipe sensors with a more robust acquisition algorithm that is adjusted for the “push”-based sensor.
2. Perform a comparative evaluation of “pull” and “push” –based swipe sensors embedded in portable devices, such as laptops, PDAs, or cell phones to broaden the scope to devices that are not stand alone USB fingerprint sensors.
3. Replication of NIST Research. While many of the research questions discussed in the various NISTIR documents are valid and important to the biometrics community, the conclusion validity for the studies may have been violated. Therefore, once the HBSI evaluation method has been revised and updated, an active agenda is needed to replicate each of the NIST studies.

4. As discussed in the User Satisfaction HBSI Post Study Usability Questionnaire results, prior usage of the sensors used in the test may have biased the results of the survey instrument. Therefore, it would be interesting to study biometric performance and usability with a two-group design: participants who previously used the biometric devices and participants who have never used the biometric devices. This would enable the results to be analyzed by experience with the devices and remove the threat to conclusion validity.
5. Observations by the author made during the usability questionnaire raise the issue of what do participants include in their classification of “usability”. A study examining biometric usability should be performed to determine if it is based on experience with a sensor, based on visual aesthetics of a biometric sensor, or in the case of this research how the actual collected fingerprints appear to the participants. In addition, do users prefer to see an “output” such as a fingerprint image, or do they just want to see the binary result: accept or reject?
6. A better understanding of task time, usability and the impact they have on habituation is needed. It would be interesting to collect a sample population of individuals who have never used the biometric sensor under test and have them perform a think aloud or cognitive walkthrough session to better understand how individuals who have never used such devices interact with the sensors and understand what is going through their mind

during such interactions with the device. This will impact the design of sensors and training protocols.

7. Investigate other biometric modalities with the HBSI evaluation method. Once the HBSI method is revised and validated, the next question is – how generalizable is the HBSI evaluation method for other biometric modalities? Likely candidates include other biometric technologies that require physical contact with a sensor, such as vein or hand. However this maybe dictated by the industry, grants, or recommendations from the ongoing research.

5.2.3. Long Term

1. Expand the HBSI research area to Psychology. Cognitive ergonomics and psychology are completely different fields and requires a deep understanding of the literature as well as background in the area. Therefore, interdisciplinary researchers from Industrial Engineering and Psychology will be sought to continue investigating the HBSI from the cognitive perspective to see if further improvements can be made to biometric systems.
2. Standardize the HBSI Evaluation Method. If after the program of work outlined in the short and medium term recommendations warrant it, a testing standard should be proposed to the biometrics community through the INCITS M1 Biometrics group.

BIBLIOGRAPHY

BIBLIOGRAPHY

Abramov, I. (1986). U.S. Patent No. 4,577,345.

Adams, A., & Sasse, M. (1999). Users are Not the Enemy: Why Users Compromise Security Mechanisms and How to Take Remedial Measures. *Communications of the ACM, 42*(12), 41-46.

Allied Business Intelligence. (2002). Department of Homeland Security Is The Catalyst For The Biometric Industry, According To New ABI Study. Retrieved February 25, 2003, 2003, from HTTP://WWW.ALLIEDWORLD.COM/PRHTML/BIM02PR2.PDF.HTML

Allison, H. (1973). *Personal Identification*. Boston: Holbrook Press, Inc.

Andre, T., Hartson, H., & Williges, R. (2003). Determining the Effectiveness of the Usability Problem Inspector: A Theory-Based Model and Tool for Finding Usability Problems. *Human Factors, 45*(3), 455-482.

Armstrong, T. (1986). Ergonomics and cumulative trauma disorders. *Hand Clinics, 2*(3), 553-565.

Armstrong, T., & Chaffin, D. (1978a). An investigation of the relationship between displacements of the finger and wrist joints and the extrinsic finger flexor tendons. *Journal of Biomechanics, 11*, 119-128.

Armstrong, T., & Chaffin, D. (1978b). Some biomechanical aspects of the carpal tunnel. *Journal of Biomechanics, 12*, 567-570.

ASCC. (2007). *National Code of Practice for the Prevention of Musculoskeletal Disorders from Performing Manual Tasks at Work*. Canberra: Australian Safety and Compensation Council (ASCC).

Ashbaugh, D. (1991). Ridgeology. *Journal of Forensic Identification, 41*(1), 16-64.

Ashbourn, J. (2000). *Biometrics: Advanced Identity Verification: The Complete Guide*. New York: Springer-Verlag.

Asher, J., & Lauer, J. (1988). *Composition Research: Empirical Designs*. New York: Oxford University Press, Inc.

Atos Origin. (2005). *UK Passport Service Biometrics Enrolment Trial*.

Badger, D. W. (1981). *Work Practices Guide for Manual Lifting* (No. 81-122). Cincinnati: Department of Health and Human Services, National Institute for Occupational Safety and Health.

Bailey, R. (1982). *Human Performance Engineering: A Guide for System Designers*. Englewood Cliffs: Prentice Hall.

Baril-Gingras, G., & Lortie, M. (1995). The handling of objects other than boxes: univariate analysis of handling techniques in a large transport company. *Ergonomics, 38*(5), 905-925.

Barrett, W. (2000). A Survey of Face Recognition Algorithms and Testing Results. In *National Biometric Test Center Collected Works* (pp. 301-305): SJSU.

Bastien, J., & Scapin, D. (1995). Evaluating a user interface with ergonomic criteria. *International Journal of Human-Computer Interaction, 7*, 105-121.

Bastien, J., Scapin, D., & Leulier, C. (1996, April 13-18). *Looking for usability problems with the ergonomics criteria and with the ISO 9241-10 dialogue principles.* Paper presented at the CHI Conference on Human Factors in Computing Systems, Vancouver, British Columbia.

Batch, K., Millett, L., & Pato, J. (2006). *Summary of a Workshop on the Technology, Policy, and Cultural Dimensions of Biometric Systems* (No. 0-309-65787-3): National Research Council.

Beer, T., Anodenko, T., & Sears, A. (1997). *A pair of techniques for effective interface evaluation: Cognitive walkthroughs and think-aloud evaluations.* Paper presented at the Human Factors and Ergonomics 41st Annual Meeting, Santa Monica.

Berry, J., & Stoney, D. (2001). History and Development of Fingerprinting. In H. C. Lee & R. E. Gaensslen (Eds.), *Advances in Fingerprint Technology* (2 ed., pp. 1-40). Boca Raton: CRC Press.

Bhattacharya, A., & McGlothlin, J. (Eds.). (1996). *Occupational Ergonomics: Theory and Applications* (Vol. 27). New York: Marcel Dekker, Inc.

Bicz, W., Gurnienny, Z., & Pluta, M. (1995). Ultrasound sensor for fingerprints recognition. *SPIE: Optoelectronic and electronic sensors, 2634*, 104-111.

Block, E. (1969). *Fingerprinting: Magic Weapon Against Crime*. New York: David McKay Company, Inc.

Bolle, R., Connell, J., Pankanti, S., Ratha, N., & Senior, A. (2004). *Guide to Biometrics*. New York: Springer.

Bone, M., & Blackburn, D. (2002). *Face Recognition at a Chokepoint: Scenario Evaluation Results*. Dahlgren: DoD Counterdrug Technology Development Program Office.

Booth, P. (1989). *An Introduction to Human-Computer Interaction*. London: Lawrence Erlbaum Associates.

Bouchier, F., Ahrens, J., & Wells, G. (1996). *Laboratory evaluation of the iris scan prototype biometric identifier* (No. SAND96-1033). Albuquerque: Sandia National Laboratories.

Bureau of Labor Statistics. (2004, December 2). Standard Occupational Classification (SOC) User Guide.   Retrieved September 20, 2007, from HTTP://WWW.BLS.GOV/SOC/SOCGUIDE.HTM

Burke, J. (2006). AuthenTec Ships Record 10 Million Biometric Fingerprint Sensors.   Retrieved August 10, 2006, from HTTP://WWW.AUTHENTEC.COM/NEWS.CFM?NEWSID=217

Chignell, M., & Hancock, P. (1992). *Design orientation and ergonomics.* Paper presented at the 1992 IEEE International Conference on Systems, Man, and Cybernetics, Chicago, IL.

Clark, A., & Clark, C. (2005). *Performance Characterization in Computer Vision: A Tutorial*. Colchester, UK: University of Essex.

Clarke, R. (1994). Human identification in information systems: Management challenges and public policy issues. *Information Technology & People, 7*(4), 6-37.

Clemmer, D. I., Mohr, D. L., & Mercer, D. J. (1991). Low-back injuries in a heavy industry I: Worker and workplace factors. *Spine, 16*(7), 824-830.

Courtney, P., & Thacker, N. (2001). Performance Characterization in Computer Vision: The Role of Statistics in Testing and Design. In J. Blanc-Talon & D. Popescu (Eds.), *Imaging and Vision Systems: Theory, Assessment, and Applications* (Vol. 9, pp. 109-128). Commack: NOVA Science Publishers.

Coventry, L., De Angeli, A., & Johnson, G. (2003a). Biometric Verification at a Self Service Interface. In P. McCabe (Ed.), *Contemporary Ergonomics 2003* (pp. 247-252). London: Taylor and Francis.

Coventry, L., De Angeli, A., & Johnson, G. (2003b, April 5-10, 2003). *Usability and biometric verification at the ATM interface.* Paper presented at the Conference on Human Factors in Computing Systems Ft. Lauderdale, Florida.

Cummins, H. (1929). *The Topographic History of the Volar Pads (Walking Pads; Tastballen) in the Human Embryo* (No. 394). Washington: Carnegie Mellon.

Cummins, H., & Wright-Kennedy, R. (1940). Purkinje's Observations (1823) on Finger Prints and Other Skin Features. *Journal of Criminal Law and Criminology, 31*(3), 343-356.

Cuomo, D., & Bowen, C. (1992). *Stages of user activity model as a basis for user-centered interface evaluation.* Paper presented at the Annual Human Factors Society Conference, Santa Monica.

Cuomo, D., & Bowen, C. (1994). Understanding usability issues addressed by three user-system interface evaluation techniques. *Interacting with Computers, 6*(1), 86-108.

Damkot, D. K., Pope, M. H., Lord, J., & Frymoyer, J. W. (1984). The relationship between work history, work environment and low-back pain in men. *Spine, 9*(4), 395-399.

Damlund, M., Goth, S., Hasle, P., & Munk, K. (1986). Low back strain in Danish semiskilled construction work. *Applied Ergonomics, 17*(1), 31-39.

Deane, F., Barrelle, K., Henderson, R., & Mahar, D. (1995). Perceived acceptability of biometric security systems. *Computers & Security, 14*, 225-231.

Deane, F., Henderson, R., Mahar, D., & Saliba, A. (1995). Theoretical Examination of the Effects of Anxiety and Electronic Performance Monitoring on Behavioural Biometric Security Systems *Interacting with Computers, 7*(4), 395-411.

Department of Health and Human Services. (1997). *Part II: Department of Health and Human Services - 21 CFR Part 11: Electronic Records; Electronic Signatures; Final Rule*. Retrieved. from HTTP://WWW.FDA.GOV/ORA/COMPLIANCE_REF/PART11/.

Desurvire, H., Kondziela, J., & Atwood, M. (1992). What is gained and lost when using evaluation methods other than empirical testing. In A. Monk, D. Diaper & M. Harrison (Eds.), *People and computers Volume VII* (pp. 89-102). Cambridge: Cambridge University Press.

Desurvire, H., & Thomas, J. (1993). *Enhancing the performance of interface evaluators.* Paper presented at the 37th Annual Human Factors and Ergonomics Society Meeting, Seattle.

Doddington, G., Kamm, T., Martin, A., Ordowski, M., & Przybocki, M. (1997). *The DET curve in assessment of detection task performance.* Paper presented at the Eurospeech, Greece.

Doubleday, A., Ryan, M., Springett, M., & Sutcliffe, A. (1997). *A comparison of usability techniques for evaluating design.* Paper presented at the Designing interactive Systems (DIS '97) Conference, Amsterdam.

Dutt, A., Johnson, H., & Johnson, P. (1994). Evaluating evaluation methods In G. Cockton, S. Draper & G. Weir (Eds.), *People and Computers, Volume IX* (pp. 109-121). Cambridge: Cambridge University Press.

Elliott, S., Kukula, E., & Modi, S. (2007). Issues Involving the Human Biometric Sensor Interface. In S. Yanushkevich, P. Wang, M. Gavrilova & S. Srihari (Eds.), *Image Pattern Recognition: Synthesis and Analysis in Biometrics* (Vol. 67, pp. 339-363). Singapore: World Scientific.

Elliott, S., Kukula, E., & Sickler, N. (2004). *The challenges of environment and the human biometric device interaction on biometric system performance.* Paper presented at the International Workshop on Biometric Technologies - Special forum on Modeling and Simulation in Biometric Technology, Calgary, Alberta, Canada.

Elliott, S., Sickler, N., Kukula, E., & Modi, S. (2005). *From Bar Codes to Biometrics: What the Practitioner Needs to Know* (3 ed.). West Lafayette: Copymat.

Faulds, H. (1880). On the Skin-furrows of the Hand. *Nature, 22*, 605.

Federal Bureau of Investigation. (1973). *The Science of Fingerprints*. Washington D.C.: U.S. Government Printing Office.

Fejfar, A., & Myers, J. (1977, July). *The testing of three automatic identity verification techniques.* Paper presented at the International Conference on Crime Countermeasures, Oxford.

Frymoyer, J. W., Pope, M. H., Costanza, M. C., Rosen, J. C., Goggin, J. E., & Wilder, D. G. (1980). Epidemiologic studies of low back pain. *Spine, 5*(5), 419-423.

Fu, L., Salvendy, G., & Turley, L. (2002). Effectiveness of user testing and heuristic evaluation as a function of performance classification. *Behaviour & information technology, 21*(2), 137-143.

Galton, F. (1892). *Finger Prints*. London: Macmillan and Co.

Garg, A., & Moore, J. S. (1992). Epidemiology of low-back pain in industry. *Occupational Medicine: State of the Art Reviews, 7*(4), 593-608.

Gould, J., & Lewis, C. (1985). Designing for Usability: Key Principles and What Designers Think. *Communications of the ACM, 2*(3), 300 - 311.

Grandjean, E. (1988). *Fitting the Task to the Man: A Textbook of Occupational Ergonomics* (4 ed.). London: Taylor & Francis.

Gray, W., & Salzman, M. (1998). Damaged merchandise? A review of experiments that compare usability evaluation methods. *Human-Computer Interaction, 13*(3), 203-261.

Greenberg, L., & Chaffin, D. (1977). *Workers and Their Tools: A Guide to the Ergonomic Design of Hand Tools and Small Presses*. Midland: Pendell Publishing Company.

Grew, N. (1684). The Description and Use of the Pores in the Skin of the Hands and Feet, by the Learned and Ingenious Nehemiah Grew, M.D. Fellow of the College of Physicians and of the Royal Society. *Philosophical Transactions, 14*, 566-567.

Gupta, B., & Kramer, A. (1999). U.S. Patent No. 5,973,623.

Hartman, J. (2000). Choosing the Correct Statistical Test. Retrieved February 21, 2007, from HTTP://BAMA.UA.EDU/~JLEEPER/627/CHOOSESTAT.HTML#OUTCOME#OUTCOME

Henderson, R., Mahar, D., Saliba, A., Deane, F., & Napier, R. (1998). Electronic Monitoring Systems: An Examination of Physiological Activity and Task Performance within a Simulated Keystroke Security and Electronic Performance Monitoring System. *International Journal of Human-Computer Studies, 48*(2), 143-157.

Herschel, W. (1880). Skin furrows of the Hand. *Nature, 23*, 76.

Hewett, T., Baecker, R., Card, S., Carey, T., Gasen, J., Mantei, M., et al. (1996, April 11, 2008). ACM SIGCHI Curricula for Human-Computer Interaction. Retrieved February 17, 2008, from HTTP://SIGCHI.ORG/CDG/INDEX.HTML

Holmes, J., Wright, L., & Maxwell, R. (1991). *A performance evaluation of biometric identification devices* (No. SAND91-0276). Albuquerque: Sandia National Laboratories.

Hoozeman, M., van der Beek, A., Frings-Dresen, M., van Dijk, F., & van der Woude, L. (1998). Pushing and pulling in relation to musculoskeletal disorders: a review of risk factors. *Ergonomics, 41*(6), 757-781.

IBG. (2003). *The Henry Classification System*. New York.

IBG. (2006). Biometrics Market and Industry Report 2006-2010. Retrieved September 12, 2006, from HTTP://WWW.BIOMETRICGROUP.COM/REPORTS/PUBLIC/MARKET_REPORT.HTML

IEEE. (1990). *IEEE Standard Computer Dictionary: A Compilation of IEEE Standard Computer Glossaries*. New York.

International Biometric Group. (2002). Global Vision for Biometrics. Retrieved April 21, 2003, 2003

International Biometric Group. (2006). Biometrics Market and Industry Report 2006-2010. Retrieved September 12, 2006, from HTTP://WWW.BIOMETRICGROUP.COM/REPORTS/PUBLIC/MARKET_REPORT.HTML

International Biometric Society. (2006, August 30, 2006). Definition of Biometrics. Retrieved September 1, 2006

International Ergonomics Association (IEA). (2006). The Discipline of Ergonomics. Retrieved January 27, 2006, 2006, from HTTP://WWW.IEA.CC/ERGONOMICS/

International Organization for Standardization. (1998). *ISO 9241: Ergonomic requirements for office work with visual display terminals (VDTs) - Part 11: Guidance on usability*. Geneva: ISO.

International Organization for Standardization. (2007). *ISO/IEC JTC1/SC37 Standing Document 2 - Harmonized Biometric Vocabulary* (No. SC37N1779). Geneva: ISO/IEC.

International Standards Organization. (2006a). *ISO/IEC 19795-1: Information technology - Biometric performance testing and reporting - Part 1: Principles and framework* (No. ISO/IEC 19795-1(E)). Geneva: ISO/IEC.

International Standards Organization. (2006b). *Software engineering - Software product Quality Requirements and Evaluation (SQuaRE) - Common Industry Format (CIF) for usability test reports* (No. ISO/IEC 25062:2006(E)). Geneva: ISO/IEC.

International Standards Organization. (2007a). *Information technology - Biometric performance testing and reporting - Part 2: Testing methodologies for technology and scenario evaluation* (No. ISO/IEC 19795-2:2007(E)). Geneva: ISO/IEC.

International Standards Organization. (2007b). *Text of DTR 19795-3, Biometric Performance Testing and Reporting – Part 3: Modality-Specific Testing* (No. 37-19795-3). Geneva: ISO/IEC.

Jain, A., Chen, Y., & Dass, S. (2005). *Fingerprint Quality Indices for Predicting Authentication Performance.* Paper presented at the 5th International Conf. on Audio- and Video-Based Biometric Person Authentication, Rye Brook, NY.

Jain, A., Pankanti, S., Prabhakar, S., Hong, L., & Ross, A. (2004, August 23-26, 2004). *Biometrics: A Grand Challenge.* Paper presented at the 17th International Conference on Pattern Recognition (ICPR 2004), Guildford, UK.

Jeffries, R., Miller, J., Wharton, C., & Uyeda, K. (1991, April 28 - May 3). *User interface evaluation in the real world: A comparison of four techniques.* Paper presented at the CHI Conference on Human Factors in Computing Systems, New Orleans.

John, B., & Marks, S. (1997). Tracking the effectiveness of usability evaluation methods. *Behaviour & information technology, 16*, 188-202.

John, B., & Mashyna, M. (1997). Evaluating a multimedia authoring tool with cognitive walkthrough and think aloud user studies. *Journal of the American Society of Information Science, 48*, 1004-1022.

Kang, K., Lee, B., Kim, H., Shin, D., & Kim, J. (2003). A Study on Performance Evaluation of Fingerprint Sensors In G. Goos, J. Hartmanis & J. van Leeuwen (Eds.), *Audio- and Video-Based Biometric Person Authentication* (pp. 574-583). Berlin / Heidelberg: Springer

Karat, C., Campbell, R., & Fiegel, T. (1992). *Comparison of empirical testing and walkthrough methods in user interface evaluation.* Paper presented at the CHI Conference on Human Factors in Computing Systems, Monterey.

Kelsey, J. L., Golden, A. L., & Mundt, D. J. (1990). Low-back pain/prolapsed lumbar intervertebral disc. *Rheumatic Disease Clinics of North America, 16*, 699-716.

Kenyon, K. (1970). *Archaeology in the Holy Land*. London: Ernest Benn.

Killen, D. (1973). U.S. Patent No. 3,781,855.

Kirakowski, J. (2007, April 20, 2007). The Use of Questionnaire Methods for Usability Assessment. Retrieved January 20, 2008, from HTTP://WWW.UCC.IE/HFRG/QUESTIONNAIRES/SUMI/SUMIPAPP.HTML

Klein, B. P., Jensen, R. J., & Sanderson, L. M. (1984). Assessment of workers' compensation claims for back strains/sprains. *Journal of Occupational Medicine, 26*(6), 443-448.

Kleinbaum, D., Kupper, L., Muller, K., & Nizam, A. (1998). *Applied regression analysis and other multivariable methods* (3rd ed.). Pacific Grove: Duxbury Press.

Kruskal, W., & Wallis, W. (1952). Use of ranks on one-criterion variance analysis. *Journal of the American Statistical Association, 47*, 583-621.

Kruskal, W., & Wallis, W. (1953). Errata to Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association, 48*, 907-911.

Kukula, E. (2007, November 7-8). *Understanding the Impact of the Human-Biometric Sensor Interaction and System Design on Biometric Image Quality.* Paper presented at the NIST Biometric Quality Workshop II, Gaithersburg, MD.

Kukula, E., & Elliott, S. (2003). *Securing a Restricted Site - Biometric Authentication at Entry Point.* Paper presented at the IEEE 37th International Carnahan Conference on Security Technology, Taiwan, ROC.

Kukula, E., & Elliott, S. (2004, October 11 - 14). *Effects of Illumination Changes on the Performance of Geometrix FaceVision 3D FRS.* Paper presented at the 38th Annual 2004 International Carnahan Conference on Security Technology (ICCST), Albuquerque, New Mexico.

Kukula, E., & Elliott, S. (2005). *Implementation of Hand Geometry at Purdue University's Recreational Center: An Analysis of User Perspectives and System Performance.* Paper presented at the 39th International IEEE Carnahan Conference on Security Technology, Las Palmas de Gran Canaria, Spain.

Kukula, E., & Elliott, S. (2006, October 16-19, 2006). *Implementing ergonomic principles in a biometric system: A look at the Human Biometric Sensor Interaction (HBSI).* Paper presented at the 40th International IEEE Carnahan Conference on Security Technology, Lexington, KY.

Kukula, E., Elliott, S., & Duffy, V. (2007, July 22-27). *The Effects of Human Interaction on Biometric System Performance* Paper presented at the 12th International Conference on Human-Computer Interaction and 1st International Conference on Digital-Human Modeling, Beijing, China.

Kukula, E., Elliott, S., Kim, H., & San Martin, C. (2007, May 17-20). *The Impact of Fingerprint Force on Image Quality and the Detection of Minutiae.* Paper presented at the 2007 IEEE International Conference on Electro/Information Technology, Chicago, IL.

Kukula, E., Elliott, S., Senarith, P., & San Martin, C. (2006). Biometrics and Manufacturing: A Recommendation of Working Height to Optimize Performance of a Hand Geometry Machine (pp. 18): Purdue University Biometrics Standards, Performance, & Assurance Laboratory.

Kukula, E., Elliott, S., Tamer, S., & Senarith, P. (2007). Biometrics and Manufacturing: A Recommendation of Working Height to Optimize Performance of a Hand Geometry Machine (pp. 18): Purdue University Biometrics Standards, Performance, & Assurance Laboratory.

Kukula, E., Elliott, S., Wolleschensky, L., Parsons, M., & Whitaker, M. (2007). Analysis of Performance and Usability of Small-Area and Swipe Fingerprint Sensors Using FTA and FTE (pp. 14): Purdue University.

Lee, H. C., Palmbach, T., & Miller, R. (2003). *Henry Lee's Crime Scene Handbook*. London: Academic Press.

Levine, J., Schappert, M., Ratha, N., Bolle, R., Pankanti, S., Germain, R., et al. (2000).

Lewis, J. R. (1993). *IBM Computer Usability Satisfaction Questionnaires: Psychometric Evaluation and Instructions for Use* (No. 54.786). Boca Raton: IBM Human Factors Group.

Lim, E., Jiang, X., & Yau, W. (2002). *Fingerprint quality and validity analysis.* Paper presented at the 2002 International Conference on Image Processing.

Maier, F., & Karageorghis, V. (1984). *Paphos: History and archaeology*. Switzerland: A.G. Leventis Foundation.

Mainguet, J. (2006). Fingerprint, palmprint, pores. Retrieved October 2, 2006, from HTTP://PERSO.ORANGE.FR/FINGERCHIP/BIOMETRICS/TYPES/FINGERPRINT.HTM

Mainguet, J., Pegulu, M., & Harris, J. (1999, October 28). *FingerChip™: Thermal imaging and finger sweeping in a silicon fingerprint sensor.* Paper presented at the IEEE AutoID 1999, Summit, NJ.

Maio, D., Maltoni, D., Cappelli, R., Wayman, J., & Jain, A. (2000). *FVC2000: Fingerprint Verification Competition*. Cesena, Italy: University of Bologna.

Mansfield, A., Kelly, G., Chandler, D., & Kane, J. (2001). *Biometric product testing final report 1.0*. Teddington: NPL.

Mansfield, A., & Wayman, J. (2002). *Best Practices in Testing and Reporting Performances of Biometric Devices*: Biometric Working Group.

Maple, C., & Norrington, P. (2006, April 20-22, 2006). *The Usability and Practicality of Biometric Authentication in the Workplace.* Paper presented at the First International Conference on Availability, Reliability and Security (ARES'06), Vienna, Austria.

Martin, J. B., & Chaffin, D. B. (1972). Biomechanical computerized simulation of human strength in sagittal plane activities. *American Institute of Industrial Engineering Transactions, 4*(1), 19-28.

Mayhew, D. (1999). *The Usability Engineering Lifecycle*. San Francisco: Morgan Kaufmann.

Micheals, R., Stanton, B., Theofanos, M., & Orandi, S. (2006). *A Taxonomy of Definitions for Usability Studies in Biometrics* (No. NISTIR 7378). Gaithersburg: NIST.

Minitab. (2000). Minitab User's Guide 2. Release 13. Retrieved June 7, 2006, 2006, from HTTP://MATHSTAT.CARLETON.CA/~HELP/MINITAB/STNONPAR.PDF

Modi, S., & Elliott, S. (2006a). *Graduate Course Development focusing on Security Issues for Professionals Working in the Manufacturing Industry.* Paper presented at the World Conference on Engineering Technology Education, Santos, Brazil.

Modi, S., & Elliott, S. (2006b). *Impact of Image Quality on Performance: Comparison of Young and Elderly Fingerprints.* Paper presented at the 6th International Conference on Recent Advances in Soft Computing (RASC 2006), Canterbury, UK.

Moggridge, B. (2007). *Designing Interactions*. Cambridge: The MIT Press.

Montgomery, D. (1997). *Design and Analysis of Experiments* (4th ed.). New York: John Wiley and Sons.

Moore, K., & Dalley, A. (2006). *Clinically Oriented Anatomy* (5 ed.). Philadelphia: Lippincott Williams and Wilkins.

Morland, N. (1950). *An Outline of Scientific Criminology* (1st ed.). New York: Philosophical Library, Inc.

Morland, N. (1971). *An Outline of Scientific Criminology* (2 (revised) ed.). London: Cassell and Company, Ltd.

Nadeau, S., & Gagnon, M. (1996). Work and energy transfers in maximal pushing of loads. *International Journal of Industrial Ergonomics, 17*(3), 221-234.

Neher, D. (2003, September 8, 2003). Transformations - What to do when Data Breaks the Rules. Retrieved December 10, 2003, 2003, from HTTP://WWW.EEESCIENCE.UTOLEDO.EDU/FACULTY/NEHER/BIOSTATISTICS/TRANSFRM.PDF

Nielsen, J. (1990). Evaluating the thinking aloud technique for use by computer scientists. In H. Hartson & D. Hix (Eds.), *Advances in human-computer interaction* (pp. 69-82). Norwood: Ablex.

Nielsen, J. (1992). *Finding usability problems through heuristic evaluation.* Paper presented at the CHI Conference on Human Factors in Computing Systems, Monterey.

Nielsen, J., & Molich, R. (1990). *Heuristic evaluation of user interfaces.* Paper presented at the CHI Conference on Human Factors in Computing Systems, Seattle.

NIOSH. (1997). Elements of Ergonomics Programs: A Primer Based on Workplace Evaluations of Musculoskeletal Disorders. Retrieved August 30, 2006, from HTTP://WWW.CDC.GOV/NIOSH/EPTBTR6.HTML#FIRST

NIST/SEMATECH. (2006). *e-Handbook of Statistical Methods*. Retrieved March 20, 2007, from HTTP://WWW.ITL.NIST.GOV/DIV898/HANDBOOK/.

Patton, M. (2002). *Qualitative Research & Evaluation Methods* (3 ed.). Thousand Oaks: Sage Publications.

Pheasant, S. (2006). *Bodyspace: Anthropometry, Ergonomics, and the Design of Work* (3rd ed.). Boca Raton: Taylor and Francis.

Phillips, P., Grother, P., Bone, M., Micheals, R., Blackburn, D., & Tabassi, E. (2003). *Face Recognition Vendor Test 2002*: DARPA, NIST, DoD, NAVSEA.

Phillips, P., Rauss, P., & Der, S. (1996). *FERET (Face Recognition Technology) Recognition Algorithm Development and Test Report* (No. ARL-TR-995): U.S. Army Research Laboratory.

Pope, M. H. (1989). Risk indicators in low back pain. *Annals of Medicine, 21*(5), 387-392.

Rabjerg, L., Jennum, P., & Morck, H. (1983). White lead exposure among Danish police officers employed in fingerprint detection. *Scandinavian Journal of Work, Environment, and Health, 9*(6), 511-513.

Rempel, D., Kier, P., Smutz, W., & Hargens, A. (1997). Effects of static fingertip loading on carpal tunnel pressure. *Journal of Orthopaedic Research, 15*, 422-426.

Riihimäki, H. (1991). Low-back pain, its origin and risk indicators. *Scandinavian Journal of Work Environment and Health, 17*(2), 81-90.

Rood, E., & Jain, A. (2003). *Biometric Research Agenda: Report of the NSF Workshop* (No. EIA-0240689). Morgantown: National Science Foundation.

Rubin, R. (1994). *Handbook of Usability Testing: How to Plan, Design, and Conduct Effective Tests*. New York: John Wiley and Sons, Inc.

Salvendy, G. (1971). Hand Size and Assembly Performance. *AIIE Transactions, 3*(1), 32-36.

Sarbanes-Oxley Act of 2002, (2002).

Schoenmarklin, R., & Marras, W. (1990). *A dynamic biomechanical model of the wrist joint.* Paper presented at the 34th Annual Meeting of the Human Factors Society, Orlando, Florida.

Schuckers, M. (2008). Purdue FTA Collaboration Update. Canton.

Sears, A. (1997). Heuristic Walkthroughs: Finding the problems without the noise. *International Journal of Human-Computer Interaction, 9*, 213-234.

Sekaran, U. (2003). *Research Methods for Business: A Skill Building Approach* (4th ed.). New York: John WIley & Sons,.

Setlak, D. (2004). Advances in Fingerprint Sensors Using RF Imaging Techniques. In N. Ratha & R. Bolle (Eds.), *Automatic Fingerprint Recognition Systems* (pp. 27-53). New York: Springer-Verlag.

Sickler, N., & Elliott, S. (2005). *An evaluation of fingerprint image quality across an elderly population vis-a-vis an 18-25 year old population.* Paper presented at the 39th Annual International Carnahan Conference on Security Technology (ICCST), Las Palmas de Gran Canaria, Spain.

Smith, S. (2003). Humans in the Loop: Human-Computer Interaction and Security. *IEEE Security and Privacy, 1*(3), 75-79.

Snook, S. H. (1978). The design of manual handling tasks. *Ergonomics, 21*(12), 963-985.

Standring, S. (Ed.). (2004). *Gray's Anatomy: The Anatomical Basis of Clinical Practice* (39 ed.). Edinburgh: Elsevier Churchill Livingstone.

Swartz, M. (2001). *Textbook of Physical Diagnosis, History and Examination* (4 ed.). Philadelphia: Saunders.

Tabachnick, B., & Fidell, L. (1996). *Using Multivariate Statistics* (3rd Edition ed.). New York: HarperCollins Publishers Inc.

Tabassi, E., & Wilson, C. L. (2005). *A novel approach to fingerprint image quality.* Paper presented at the International Conference on Image Processing, Genoa, Italy.

Tayyari, F., & Smith, J. (2003). *Occupational Ergonomics: Principles and Applications*. Norwell: Kluwer Academic Publishers.

Thatcher, A., James, J., & Todd, A. (2005). *Pushing vs. Pulling Strength: Effect of Handle Height and Practical Ergonomics Applications.* Paper presented at the Fourth International Cyberspace Conference on Ergonomics (CybErg), Johannesburg.

Theofanos, M., Micheals, R., Scholtz, J., Morse, E., & May, P. (2006, April 22-27, 2006). *Does habituation affect fingerprint quality?* Paper presented at the Conference on Human Factors in Computing Systems Montréal, Québec, Canada

Theofanos, M., Orandi, S., Micheals, R., Stanton, B., & Zhang, N. (2006). *Effects of Scanner Height on Fingerprint Capture* (No. NISTIR 7382). Gaithersburg: National Institute of Standards and Technology.

Theofanos, M., Stanton, B., Orandi, S., Micheals, R., & Zhang, N. (2007). *Usability Testing of Ten-Print Fingerprint Capture* (No. NISTIR 7403). Gaithersburg: NIST.

Thomas, G. (1978). The physics of fingerprints and their detection. *Physics E Scientific Instruments, 11*(8), 722-731.
Todd, A. (2005). Current trends in research focused on pushing and pulling. *Ergonomics SA: Journal of the Ergonomics Society of South Africa, 17*(2), 42-53.
Torpey, F. (1995). Data from FBI's Identification Division Automated Services database of 22,000,000 human-classified fingerprint records: Mitre Corporation.
Tsikos, C. (1982). U.S. Patent No. 4,353,056.
U.S. National Library of Medicine. (2006, June 15, 2006). Visible Proofs: Forensic Views of the Body. Retrieved April 2, 2007, from HTTP://WWW.NLM.NIH.GOV/VISIBLEPROOFS/GALLERIES/BIOGRAPHIES/BERTILLON.HTML
UPEK Inc. (2007). Chipsets and Sensors. Retrieved August 21, 2007, from HTTP://WWW.UPEK.COM/SOLUTIONS/PHYSICAL/CHIPSETS_SENSORS.ASP#TABLE1
Virzi, R. (1990). *Streamlining the design process: Running fewer subjects.* Paper presented at the 34th Annual Meeting of the Human Factors and Ergonomics Society, Santa Monica.
Virzi, R. (1992). Refining the test phase of usability evaluation: How many subjects is enough? *Human Factors, 34*(4), 457-468.
Virzi, R., Sorce, J., & Herbert, L. (1993). *A comparison of three usability evaluation methods: Heuristic, think-aloud, and performance testing.* Paper presented at the 36th Annual Meeting of the Human Factors and Ergonomics Society, Seattle.
Wayman, J. (2000). Multi-Finger Penetration Rate and ROC Variability for Automatic Fingerprint Identification Systems. In J. Wayman (Ed.), *National Biometric Test Center Collected Works 1997-2000* (1.2 ed., pp. 179-190). San Jose.
Weiss, N., Bloom, T., & Rempel, D. (1992). Wrist Position of Lowest Carpal Tunnel Pressure: A New Method to Measure Intracarpal Pressure as a Function of Wrist Position. *Journal of Bone and Joint Surgery*.
Woodson, W. (1982). *Human Factors Design Handbook: Information and Guidelines for the Design of Systems, Facilities, Equipment, and Products for Human Use*. New York: McGraw-Hill.
Yao, M., Pankanti, S., & Haas, N. (2004). Fingerprint Quality Assessment. In N. Ratha & R. Bolle (Eds.), *Automatic Fingerprint Recognition Systems* (pp. 55-66). New York: Springer.
Young, J. (2005). *Portable Biometrics Workstation: Session Interface*. Gaithersburg: NIST.
Young, M., & Elliott, S. (2007, June 7-8). *Image Quality and Performance Based on Henry Classification and Finger Location.* Paper presented at the IEEE Workshop on Automatic Identification Advanced Technologies, Alghero, Italy.

Zevecic, A., Miller, D. I., & Harburn, K. (2000). An Evaluation of the Ergonomics of Three Computer Keyboards. *Ergonomics, 43*(1), 55-72.
Zhang, S. (1999). *An Atlas of Histology*. New York: Springer Verlag.
Zwiesele, A., Munde, A., Busch, C., & Daum, H. (2000). *BioIS Study. Comparative Study of Biometric Identification Systems.* Paper presented at the IEEE 34th Annual 2000 International Carnahan Conference, Ottawa, Ontario.

APPENDICES

Appendix A. HBSI Post-Study Usability Questionnaire and Instructions

HBSI post study usability questionnaire adapted from Lewis (1993)	Original items from the PSSUQ (Lewis, 1993)
1. Overall, I am satisfied with how easy it is to use the _____ sensor.	1. Overall, I am satisfied with how easy it is to use this system.
2. It was simple to use the ____ sensor.	2. It was simple to use this system.
3. I could effectively complete the task using the ____ sensor.	3. I could effectively complete the tasks and scenarios using this system.
4. I was able to complete the task quickly using the ____ sensor.	4. I was able to complete the tasks and scenarios quickly using this system.
5. I was able to efficiently complete the task using the ____ sensor.	5. I was able to efficiently complete the tasks and scenarios using this system.
6. I felt comfortable using the ____ sensor.	6. I felt comfortable using this system.
7. It was easy to learn to use the ____ sensor.	7. It was easy to learn to use this system.
8. I believe I could become productive quickly using the ____ sensor.	8. I believe I could become productive quickly using this system.
Note: Cues include visual or tactile reminders, prompts, or indicators that help you interact with a system or device. 9. The ____ sensor clearly provided cues to remind me how to use it.	9. The system gave error messages that clearly told me how to fix problems.
10. Whenever I performed a swipe with my finger that did not capture using the ____ sensor, I could recover easily and quickly.	10. Whenever I made a mistake using the system, I could recover easily and quickly.
11. The ____ sensor design provided cues that were clear.	11. The information (such as on-line help, on-screen messages and other documentation) provided with this system was clear.
12. It was easy to find where I needed to place my finger on the ______ sensor.	12. It was easy to find the information I needed.

13. The cues of the _____ sensor were easy to understand.	13. The information provided for the system was easy to understand.
14. The design of the _____ sensor was effective in helping me complete the task.	14. The information was effective in helping me complete the tasks and scenarios.
15. The organization of information on the ____ sensor was clear.	15. The organization of information on the system screens was clear.
	Note: The interface includes those items that you use to interact with the system. For example, some components of the interface are the keyboard, the mouse, the screens (including their use of graphics and language).
16. My interaction with the ____ sensor was pleasant.	16. The interface of this system was pleasant.
17. I liked using the ____ sensor.	17. I liked using the interface of this system.
18. The ____ sensor has all the functions and capabilities I expect it to have.	18. This system has all the functions and capabilities I expect it to have.
19. Overall, I am satisfied with the ____ sensor.	19. Overall, I am satisfied with this system.

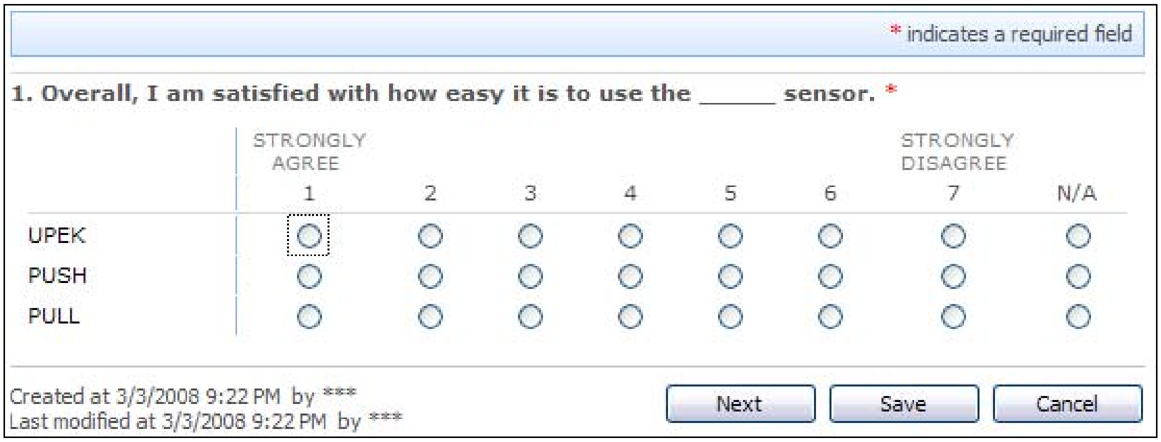
Survey Instructions Provided to the Participant

Thank you for completing all three visits of my study.

This questionnaire, which starts on the computer in front of you, gives you an opportunity to tell us your reactions to each of the 3 swipe sensors you used: UPEK, PUSH, & PULL.

Your responses will help us understand what aspects of the swipe sensors you are particularly concerned about and the aspects that satisfy you.

Please read each statement and indicate how strongly you agree or disagree with the statement for each swipe sensor by selecting the number on the scale for each of the 19 questions, as shown below. If a statement does not apply to you, select N/A.



* indicates a required field

1. Overall, I am satisfied with how easy it is to use the ______ sensor. *

	STRONGLY AGREE 1	2	3	4	5	6	STRONGLY DISAGREE 7	N/A
UPEK	○	○	○	○	○	○	○	○
PUSH	○	○	○	○	○	○	○	○
PULL	○	○	○	○	○	○	○	○

Created at 3/3/2008 9:22 PM by ***
Last modified at 3/3/2008 9:22 PM by ***

Next Save Cancel

If you have comments for a particular sensor, question, or about the study, the last question is an open space for you to type or elaborate on your choices.

After you have completed this online questionnaire please notify me and we will finish filing the payment forms.

Thank you!

UPEK PUSH PULL

Figure 118 Image of 3 swipe sensors provided on the computer screen during the visit 3 usability questionnaire.

Appendix B. Questions and actions that may occur during the test session with a participant. Partially based upon Theofanos, Stanton, Orandi, et al. (2007).

	Participant	**Researcher response/action**
Questions	The participant asks "can I begin now"	If you are ready, please continue
	General questions about the directions for swiping/placing their digits on the sensor	You should perform as the instructions indicated.
	What does _______ do? The sensor, software, etc…	Don't explain I'd be happy to explain at the end of the test.
	Is the scanner clean?	Only __ participants have used it so far. Explain research on cleanliness of devices.
	May I see the instructions again?	You may see the instructions again after the last interaction with this sensor.
	Why is the scanner/ should the scanner be warm?	This is normal system behavior.
	Can I move the sensor?	Yes, you may position the sensor anywhere in the designated box.
	Can I take a break?	Would you mind completing the interactions for this sensor first? No. Pause on completion. Yes. Please click the pause button on the screen.
Actions	Participant attempts wrong task, but does not notice.	If the participant uses the incorrect hand/finger, but does not notice, make the correction after the participant completes 3-4 error producing interactions with that sensor.
	Participant notices they have attempted the wrong task and explicitly states the fact.	Researcher should cancel/stop the step in process and state "Please wait while I make a correction".

	Participant thinks they have used the incorrect hand or made a mistake but has not.	Tell the participant to continue with the rest of the tasks and that they can try again after completing the current tasks. If done correctly, inform they did not make a mistake and proceed to the next step. If they did make a mistake, document the error and have them restart the interaction for that particular sensor.
	Participant leaves their hand on too long.	State the appropriate response: You may remove your hand now.
	Participant swipes too slow/fast, wrong part of their finger, etc…	If the participant does not notice, make the correction after the participant completes that sensor, after it times out, or provide assistance after 3-4 incorrect interactions. Have them redo the interactions correctly before clicking the end session timer for that particular sensor.
	Participant lifts their hand/finger too soon and goes on to the next task.	No verbal correction, but document interaction as such.
	Participant lifts their hand too soon then replaces it again.	This will be marked as an interaction error.
	Participant assumes they are done	If the participant thinks they completed a session/interaction and did not, mark as a failure to complete. Restart capture sequence and ask if they would mind interacting with the sensor again.
	Participant asks if they are done.	Ask if they would please complete the current set of interactions and then discuss remaining items to complete. If they would like to discontinue use, state that they could withdraw at any time.
	Test Administrator error	If the test administrator performed an error during data collection, it was noted by the hand appearing in the video area for 1-2 seconds. After such action occurred, the appropriate corrective action was taken.

	Timeout	If the system times out, record if it was due to error, software, or the user. Ask the user to try again (up to three times per sensor/finger)

Appendix C. Qualitative Data Collection Consent Form

For IRB Office Use Only

Research Project Number: ________________

RESEARCH PARTICIPANT CONSENT FORM
Feedback on User Experiences with Fingerprint Recognition

Stephen J. Elliott, Ph.D.
Purdue University - Department of Industrial Technology

Purpose of Research
The purpose of this study is to obtain feedback from users who have interacted with fingerprint sensors, whether in everyday life, participating in previous research, or any other means to understand problems, concerns, and to obtain feedback on how users feel the design of the sensors could be improved.

Specific Procedures to be Used
1. I understand that I will first be verbally briefed on the purpose and procedures of the study to inform me of what data will be collected. If I agree to participate I will sign the consent form. I understand this study will take no longer than 15-20 minutes and depends on the length of my answers.
2. I understand the following demographic information will be collected: gender, occupation, ethnicity, age, handedness, questions about familiarity with biometrics, and if I have musculoskeletal ailments.
3. Next, the test administrator will start the audio and video recording. The video recording will be setup so the participant's face is not in the field of view of the camera. The audio will record both the test administrator and my voice so that my answers can be examined at a later time. I understand that there is no wrong answer and that this evaluation is interested only in my thoughts and opinions regarding fingerprint recognition devices. The videotape will record the specific way in which I demonstrate to the test administrator how I would like the fingerprint sensor to function or any suggestions I have for its operation, etc…
4. Next, the test administrator will ask me questions about my thoughts about the effectiveness and efficiency, attitudes, and satisfaction with regards to the fingerprint recognition devices the I've used. These questions will be open ended and I will have the opportunity to demonstrate with the sensors what I am talking about if I wish to or have issues putting in words what I am talking about.
5. Next, I will be asked if I were going to design a device or have someone else do it, what I would change or how they would design it, and why.
6. I understand I can be asked any follow-on questions regarding my feedback and opinions about the fingperprint devices, but can deny to answer any question and can withdraw from the study at any time.
7. Lastly, I understand the data of all the participants will be analyzed together to see if there are any common themes across the responses, which could be used in the future to design a fingerprint device, or if there are common concerns or feelings with regards to using the devices.

Risks to the Individual
I understand that this study will have minimal risk on me, that is no more than I would encounter in everyday life.

Benefits to the Individual
I understand that there are no direct benefits for me, the participant at this time. However, the evaluation of new technologies for future applications in security and access control, as well as identifying individuals, impostors and frauds out of secure areas, could be immeasurable in the future.

Compensation
I understand that there is NO compensation for this study.

Confidentiality
I understand that a unique identification number will be given to me. I understand, this number will be associated with the audio and video data stored on the storage media along with the demographic information. My name will not be associated with any of the data collected in this study. The project's research records may be inspected by the Purdue University Institutional Review Board to ensure that participants' rights are being protected. Audio and video data collected are only statements, opinions, and actions of the participant, however the data will be secured in Room 378 Knoy Hall, which is assessable by key and biometric access control. The data will be kept indefinitely for analysis purposes, but will not be used in future research. Access to the audio and video data will be limited to the Principal Investigator (PI) and the Co-investigator (Co-I) Eric Kukula. At any time a subject wishes to cease participation, the PI will delete all recorded audio/video data of the subject, and the subject will sign that they have witnessed the destruction.

Voluntary Nature of Participation
I do not have to participate in this research project. If I agree to participate, I can withdraw my participation at any time without penalty.

Human Subject Statement:
If I have any questions about this research project, I can contact Stephen J. Elliott by phone (494-2311) or by email elliott@purdue.edu. If I have concerns about the treatment of research participants, I can contact the Committee on the Use of Human Research Subjects at Purdue University, 610 Purdue Mall, Hovde Hall Room 307, West Lafayette, IN 479072040. The phone number for the Committee's secretary is (765) 494-5942. The email address is irb@purdue.edu.

I HAVE HAD THE OPPORTUNITY TO READ THIS CONSENT FORM, ASK QUESTIONS ABOUT THE RESEARCH PROJECT AND AM PREPARED TO PARTICIPATE IN THIS PROJECT.

Participant's Signature Date

Participant's Name Participants e-mail

INTERNAL USE ONLY

Participant ID Number

Researcher's Signature Date

Appendix D. Interview Questionnaire Guide for Biometric Users

Topic Area	Question
Usefulness / Failure to Use	1. After your experience with the device (which is in front of you) would you want to use this for everyday use with your computer? Why or why not?
Effectiveness	2. The goal of the prior studies were to collect fingerprint images in succession, meaning each time you swiped your finger across the sensor the sensor should have acquired an image. a. Think back to your visits…
	i. Were you able to complete the task?
	ii. Did you forget how to use the device?
	iii. Did you forget where to place your finger?
	iv. Did it take a while to finish your visit? (Accuracy -- FTA)
Efficiency	3. After you were instructed on how to use the devices (prior to swiping your finger), what did you think about the level of difficulty of the study (did you think it was going to be a piece of cake or wish you had time to study)?
	4. After you started using it, did your opinion change about the easiness of the study? Why?
	5. Did the devices get easier to use over time?
	6. Knowing that you had to swipe your finger across the sensor so that only the last segment of your finger creates the fingerprint image, did the design of the sensor allow for you to interact with the sensor in an efficient manner?
	a. Would you make any changes based on this?
Satisfaction	7. What did you think about the fingerprint sensor design knowing how you are supposed to use it after participating in a couple studies
	8. So did this design aid or hinder you in any way with interacting with the device?
	9. Given the swipe fingerprint sensor you used during your prior participation… and the multiple times you have used it…
	a. What did you like about the design?
	b. What did you not like about the design?
Designing a Device	10. If you were going to design a device or how would you design it, what would you change, and why? And to help you answer that, I am going to introduce some different designs that are also out there.
Final Thoughts	10. Do you have any final questions, comments, thoughts, etc…

Appendix E. Interview Questionnaire Guide for Biometric Non-Users and Ergonomic Experts

Topic Area	Question
Usefulness / Failure to Use	1. This is a fingerprint sensor (point to device).
	a. What are your first thoughts regarding this device?
Efficiency	2. How would you interact with this fingerprint device given this design? Please step me through your thought process and explain to me what you are doing.
	b. Now to train you using the method that all users received during their interactions with the sensors in the lab. To use the device correctly you only use the last segment of your finger (point to it and demo on the device) and swipe it across. As you swipe across it collects the individual pieces of the fingerprint and reconstructs the image.
Effectiveness	3. Now I am going to define the task. You need to swipe your finger across the sensor so that an image of the area of your last finger segment can be captured. So each time you swipe your finger an image is captured. You can use any of the fingers with it. Now take a few moments and swipe your finger a few more times on there if you would like.
	c. From your brief exposure to the sensor, does the design aid or hinder you in correctly swiping your finger?
	d. Are there any visual or tactile cues that you like, don't like, or find missing?
Satisfaction	4. What did you like about the fingerprint sensor design?
	5. What did you find about the sensor design that you did not care for?
Designing a Device	6. If you were going to design a device or how would you design it, what would you change, and why?
Alternative Designs	7. Now here are two alternate designs.
	a. What are your first thoughts regarding these devices?
	b. How would you interact with these devices given the design?
	c. Do these sensor designs aid or hinder you in correctly swiping your finger?

	d. Are there any visual or tactile cues that you like, don’t like, or find missing with these two designs?
	e. What did you like about these fingerprint sensor designs?
	f. What did you not like about these fingerprint sensor designs?
	9. Now if you were going to design a device, seeing a few different devices, how would you design it and why?
Final Thoughts	10. Do you have any final questions, comments, thoughts, etc…

Appendix F. Qualitative Data Collection Interview/Observation Guide

Guide 1: Fingerprint Users

Subject Number:
002

Feedback on User Experiences with Fingerprint Recognition INTERVIEW FORM

CHECKED NOV 27 2007

Demographic questions (fill in excel sheet)

Usefulness / Failure to Use

1. After your experience with the device (which is in front of you) would you want to use this for everyday use with your computer? Please specify your reasoning → technology, design, hard to use, etc...

Yes

Effectiveness

2. The goal of the prior studies were to collect fingerprint images in succession, meaning each time you swiped your finger across the sensor the sensor should have acquired an image.
   a. Think back to your visits...
      i. Were you able to complete the task?
      ii. Did you forget how to use the device?
      iii. Did you forget where to place your finger?
      iv. Did it take a while to finish your visit? (Accuracy → FTA)
      v. Were there issues with the equipment being testing during your participation?

Efficiency

3. After you were instructed on how to use the devices (prior to swiping your finger), what did you think about the level of difficulty of the study (did you think it was going to be a piece of cake or wish you had time to study)?

4. After you started using the swipe sensor, did your opinion change about the easiness of the study? Why?

5. Did the swipe sensor devices get easier to use over time?

6. During training on the swipe fingerprint devices you were instructed to only use the last segment of your finger on the swipe sensor. Did the design of the sensor allow for you to interact with the sensor easily?
   a. Would you make changes based on this?

Slope lower

Satisfaction

7. What did you think about the fingerprint sensor design knowing how you are supposed to use it after participating in a couple studies?

preferred Newer design over old sensor

8. Did the sensor design aid or hinder you in correctly swiping your finger?

Discussed alignment issue but DIDN'T Suggest design to change this

9. Given the swipe fingerprint sensor you used during your prior participation… and the multiple times you have used it…
   a. What did you like about the design?
   b. What did you not like about the design?

Designing a Device

10. If you were going to design a device or how would you design it, what would you change, and why?

Shorter
↓ slope

Final Thoughts

11. Do you have any final questions, comments, thoughts, etc…

Group 2: Ergonomic Experts

Subject Number: 20

ERGONOMIC EXPERTS - Feedback on User Experiences with Fingerprint Recognition

Demographic questions (fill in excel sheet)

Usefulness / Failure to Use

1. This is a fingerprint sensor (point to device).
   a. What are your first thoughts regarding this device?
   b. Would you use this for everyday use with your computer based upon your thoughts, feelings, beliefs?

Efficiency

2. How would you interact with this fingerprint device given this design? Please step me through your thought process and explain to me what you are doing.
   a. [If they cannot figure out what to do, i.e. treat as a LA sensor, use incorrectly] This is the fingerprint sensor (point to sensor). Now, knowing where the sensor is, how would you interact with this fingerprint device.
   b. Now to train you using the method that all users received during their interactions with the sensors in the lab. To use the device correctly you only use the last segment of your finger (point to it and demo on the device) and swipe it across. As you swipe across it collects the individual pieces of the fingerprint and reconstructs the image.

Effectiveness

3. Now I am going to define the task. You need to swipe your finger across the sensor so that an image of the area of your last finger segment can be captured. So each time you swipe your finger an image is captured. Now take a few moments and swipe your index fingers a few times...
   c. From your brief exposure to the sensor, does the design aid or hinder you in correctly swiping your finger?
   Causes to flinch
   d. Are there any visual or tactile cues that you like, don't like, or find missing?

Satisfaction

4. What did you like about the fingerprint sensor design?
   Concave
5. What did you find about the sensor design that you did not care for?
   raised nature of sensor
   → hump

Designing a Device

6. If you were going to design a device or how would you design it, what would you change, and why?

Divet on hump for concave

Alternate Designs

7. Now here are two alternate designs.
   a. What are your first thoughts regarding these devices?

Round	square
like targets	chaos

   b. How would you interact with these devices given the design?

   c. Do these sensor designs aid or hinder you in correctly swiping your finger?

   d. Are there any visual or tactile cues that you like, don't like, or find missing with these two designs?

   e. What did you like about these fingerprint sensor designs?

   f. What did you not like about these fingerprint sensor designs?

8. Of all three swipe sensors, which do you prefer?

9. Now if you were going to design a device, seeing a few different devices, how would you design it and why?

Final Thoughts

10. Do you have any final questions, comments, thoughts, etc…

Group 3: Fingerprint Non-Users

Subject Number: 30

NON-USERS - Feedback on User Experiences with Fingerprint Recognition

Demographic questions (fill in excel sheet)

Usefulness / Failure to Use

1. This is a fingerprint sensor (point to device).
   a. What are your first thoughts regarding this device?

   b. Would you use this for everyday use with your computer based upon your thoughts, feelings, beliefs?

Efficiency

2. How would you interact with this fingerprint device given this design? Please step me through your thought process and explain to me what you are doing.

   e. [If they cannot figure out what to do, i.e. treat as a LA sensor, use incorrectly] This is the fingerprint sensor (point to sensor). Now, knowing where the sensor is, how would you interact with this fingerprint device.

   f. Now to train you using the method that all users received during their interactions with the sensors in the lab. To use the device correctly you only use the last segment of your finger (point to it and demo on the device) and swipe it across. As you swipe across it collects the individual pieces of the fingerprint and reconstructs the image.

Effectiveness

3. Now I am going to define the task. You need to swipe your finger across the sensor so that an image of the area of your last finger segment can be captured. So each time you swipe your finger an image is captured. Now take a few moments and swipe your index fingers a few times...
   g. From your brief exposure to the sensor, does the design aid or hinder you in correctly swiping your finger?

   h. Are there any visual or tactile cues that you like, don't like, or find missing?

Satisfaction

4. What did you like about the fingerprint sensor design?

5. What did you find about the sensor design that you did not care for?

Designing a Device

6. If you were going to design a device or how would you design it, what would you change, and why?

Alternate Designs

7. Now here are two alternate designs.
    a. What are your first thoughts regarding these devices?

Round	square
feel comfy ced	

    b. How would you interact with these devices given the design?

    c. Do these sensor designs aid or hinder you in correctly swiping your finger?

    d. Are there any visual or tactile cues that you like, don't like, or find missing with these two designs?

    e. What did you like about these fingerprint sensor designs?

    f. What did you not like about these fingerprint sensor designs?

8. Of all three swipe sensors, which do you prefer?

9. Now if you were going to design a device, seeing a few different devices, how would you design it and why?

Final Thoughts

10. Do you have any final questions, comments, thoughts, etc…

Appendix G. Quantitative Data Collection Consent Form

For IRB Office Use Only

Research Project Number: **0604003736**

RESEARCH PARTICIPANT CONSENT FORM
UPEK Testing – (C) *Ergonomic and Usability Testing of Fingerprint Sensors*
Stephen J. Elliott, Ph.D.
Purdue University - Department of Industrial Technology

Purpose of Research
I, the participant, understand the purpose of **(C) *Ergonomic and Usability Testing of Fingerprint Sensors*** is to evaluate the ergonomics, usability, and acceptability of fingerprint sensors. This study investigates how well users, such as myself, use and interact with fingerprint sensors to determine if a particular sensor design, or parts or a sensor design are more easily used and/or preferred by those that use them.

Specific Procedures to be Used for (C) *Ergonomic and Usability Testing of Fingerprint Sensors*
I understand this study consists of 3 visits that are separated by at least 7 calendar days. After reading and signing this consent form, I understand that I will be assigned a participant identification number and this number and not my name will be the only thing associated with the data collected in this study. I understand the data being collected in this study includes:

- Background information: Gender, occupation, whether I use lotion on my hands, ethnicity, age, handedness, occupation, questions about my familiarity with biometrics, and if I have a musculoskeletal ailment. I also understand I will also be given a short series of questions that measures the level of anxiety that I am feeling. Both my hands will be scanned so that measurements can be made regarding the size of my hands. Also, skin characteristics of my fingers such as: skin surface temperature, skin moisture, elasticity, and oiliness will be measured.
- Biometric Data: Each "placement" I perform on the fingerprint sensor will result in an image of my fingerprint that will be stored on the computer hard drive for analysis.
- Video and computer screen data: I do understand by writing my initials in the box to the right that my hands will be videotaped so that the interaction between my fingers and the sensor can be evaluated at a later time. I understand the purpose of videotaping my fingers interacting with the fingerprint sensors is to study how individuals use the sensors to possibly make changes in the future, making it more comfortable and easier to use. In adition, my movements on the computer, including mouse movements and interactions will be recorded using a computer screen capture software program.

Initials:

Visit 1: Training, Enrollment and Matching — APPROXIMATE TIME: 40minutes
Before data collection begins, all the background information described above will be collected. Next, I will be shown the first sensor that I will be asked to use and told which finger (left or right index finger) the test administrator wants me to use. I will then be trained (need to provide 4 acceptable images), enrolled (need to provide 10 images), and verified (need to provide 10 images). This process will be repeated on each of the 4 SENSORS using BOTH Right and Left index fingers.

Visits 2 and 3: Matching Only — APPROXIMATE TIME: 15 minutes each
During visits 2 and 3, I understand that I will only be performing the matching portion of the test. Before data collection begins, the skin characteristics of my fingers will be measured using skin monitor and will record: temperature, skin moisture, elasticity, and oiliness of my skin. This is done each visit because these characteristics change daily. Next, I will be shown the first sensor I will use and instructed which finger to use and provide 10 verification images for each of the 4 sensors with both the left and right index finger.

Risks to the Individual
I understand that this study will have minimal risk on me, that is no more than I would encounter in everyday life. If I would like to take a break during this study, I just need to tell the test administrator. I also understand that I can withdraw from the study at any time.

Benefits to the Individual
I understand that there are no direct benefits for me, the participant at this time. However, the evaluation of new technologies for future applications in security and access control, as well as identifying individuals, impostors and frauds out of secure areas, could be immeasurable in the future.

Page 1 Participant's Initials ________________

Research Project Number: **0604003736**

Compensation

I understand that upon completion of **all 3 visits** (C) *Ergonomic and Usability Testing of Fingerprint Sensors* that I will receive $20.

Confidentiality

I understand that a unique identification number will be given to me. I understand, this number is associated with my fingerprints or hand images stored on the system along with my demographic information. I have been informed that my name will not be associated with my template (fingerprint) stored on the system. Fingerprints collected will be secured in Room 378 Knoy Hall, which is assessable by key and biometric access control. The data will be kept indefinitely. I also understand the videotape of my fingers interacting with the sensors will be stored indefinitely. Access to the fingerprint images and the stored videos of the finger interaction with the sensors will be limited to the Principal Investigator (PI), Co-investigator (Co-I) Eric Kukula, and a representative from UPEK who will have access to the data for research use only. Both the fingerprint image data and the videotape of the finger interaction with the sensors that is collected will be used for data analysis and may be used for future study as long as this IRB protocol remains open. I understand that my name will be collected and used for IRB purposes only. The project's research records may be inspected by the Purdue University Institutional Review Board or its designees and UPEK to ensure that participants' rights are being protected.

Voluntary Nature of Participation

I do not have to participate in this research project. If I agree to participate I can withdraw my participation at any time without penalty.

Human Subject Statement:

If I have any questions about this research project, I can contact Stephen J. Elliott by phone (494-2311) or by email elliott@purdue.edu. If I have concerns about the treatment of research participants, I can contact the Committee on the Use of Human Research Subjects at Purdue University, 610 Purdue Mall, Hovde Hall Room 307, West Lafayette, IN 479072040. The phone number for the Committee's secretary is (765) 494-5942. The email address is irb@purdue.edu.

I HAVE HAD THE OPPORTUNITY TO READ THIS CONSENT FORM, ASK QUESTIONS ABOUT THE RESEARCH PROJECT AND AM PREPARED TO PARTICIPATE IN THIS PROJECT.

Participant's Signature Date

Participant's Name Participants e-mail

INTERNAL USE ONLY

Participant ID Number

Researcher's Signature Date

Appendix H. Training and Acclimation Presentation

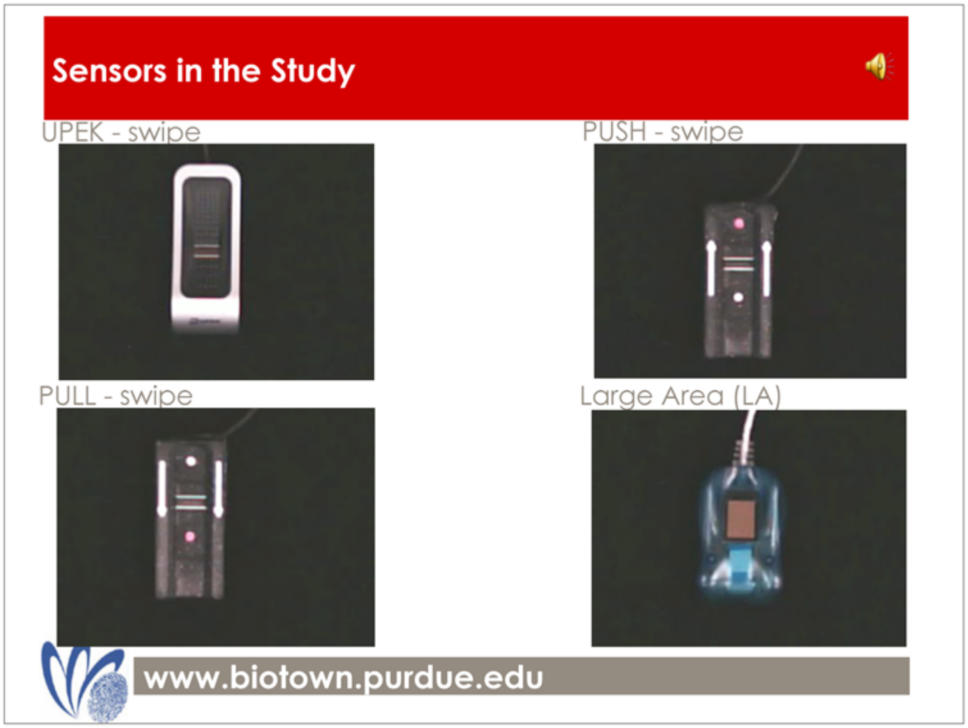
Human-Biometric Sensor Interaction Study

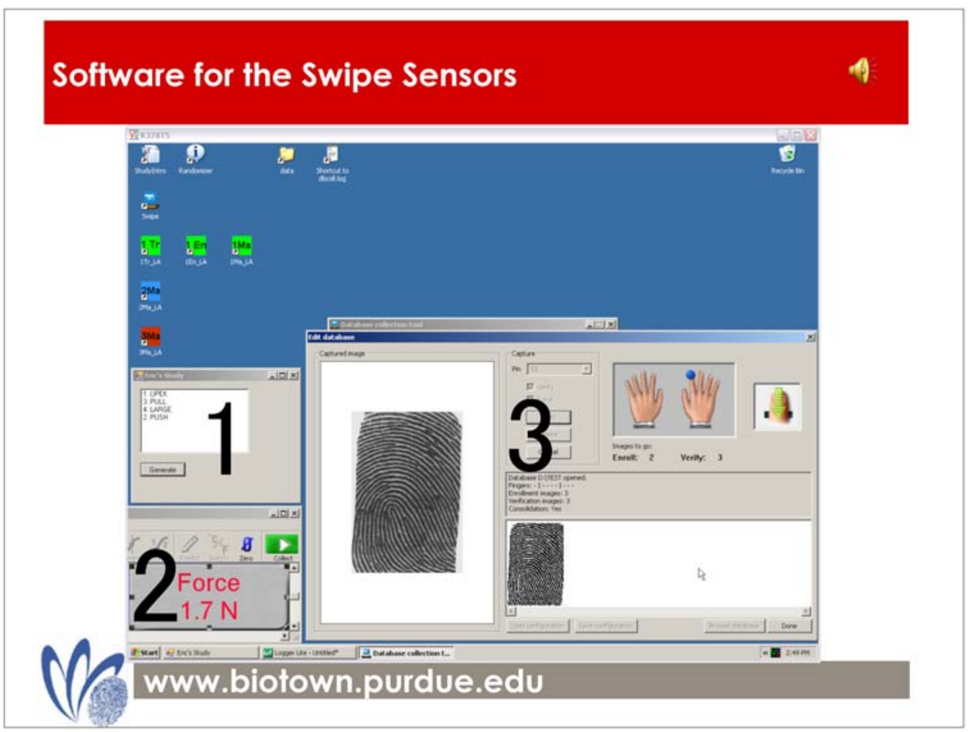
Overview of the Study… Please ask questions at any time

What you will be doing?

- Today
  - Demographic data collection
  - Learning how to use the devices (Training)
    - 2 Enrollment images, 2 matching images per sensor
  - Enrolling in the system (Enrollment)
    - 10 enrollment images per sensor, 1 matching image per sensor to verify enrollment succeeded
  - Verifying in the system (Matching)
    - 1 practice capture, 10 matching images
- Visit 2-3
  - Matching Only

www.biotown.purdue.edu


Sensors in the Study
UPEK - swipe
PUSH - swipe
PULL - swipe
Large Area (LA)
www.biotown.purdue.edu


Software for the Swipe Sensors
1
2
Force
1.7 N
3
www.biotown.purdue.edu

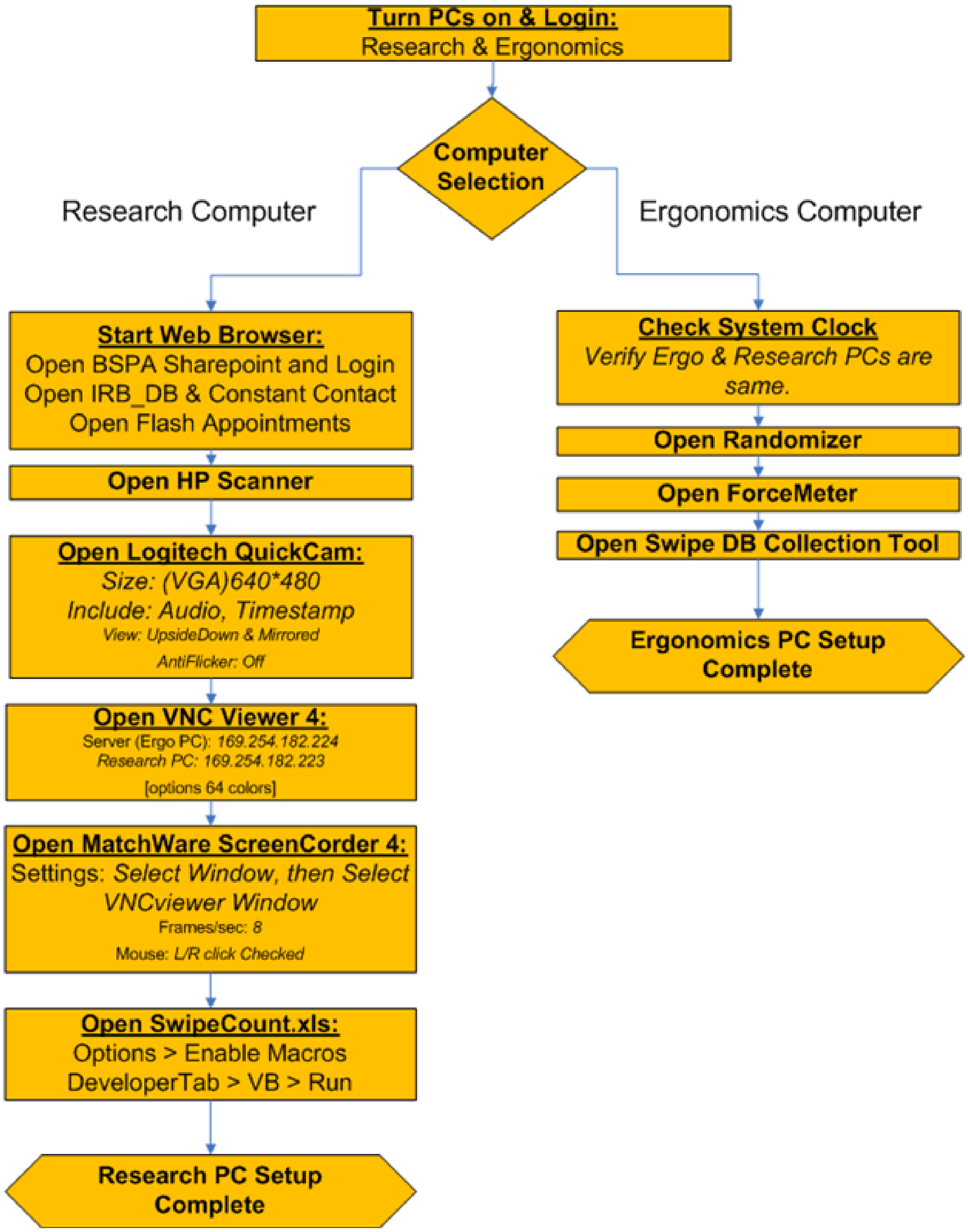
Software for the Large Area Sensor

www.biotown.purdue.edu

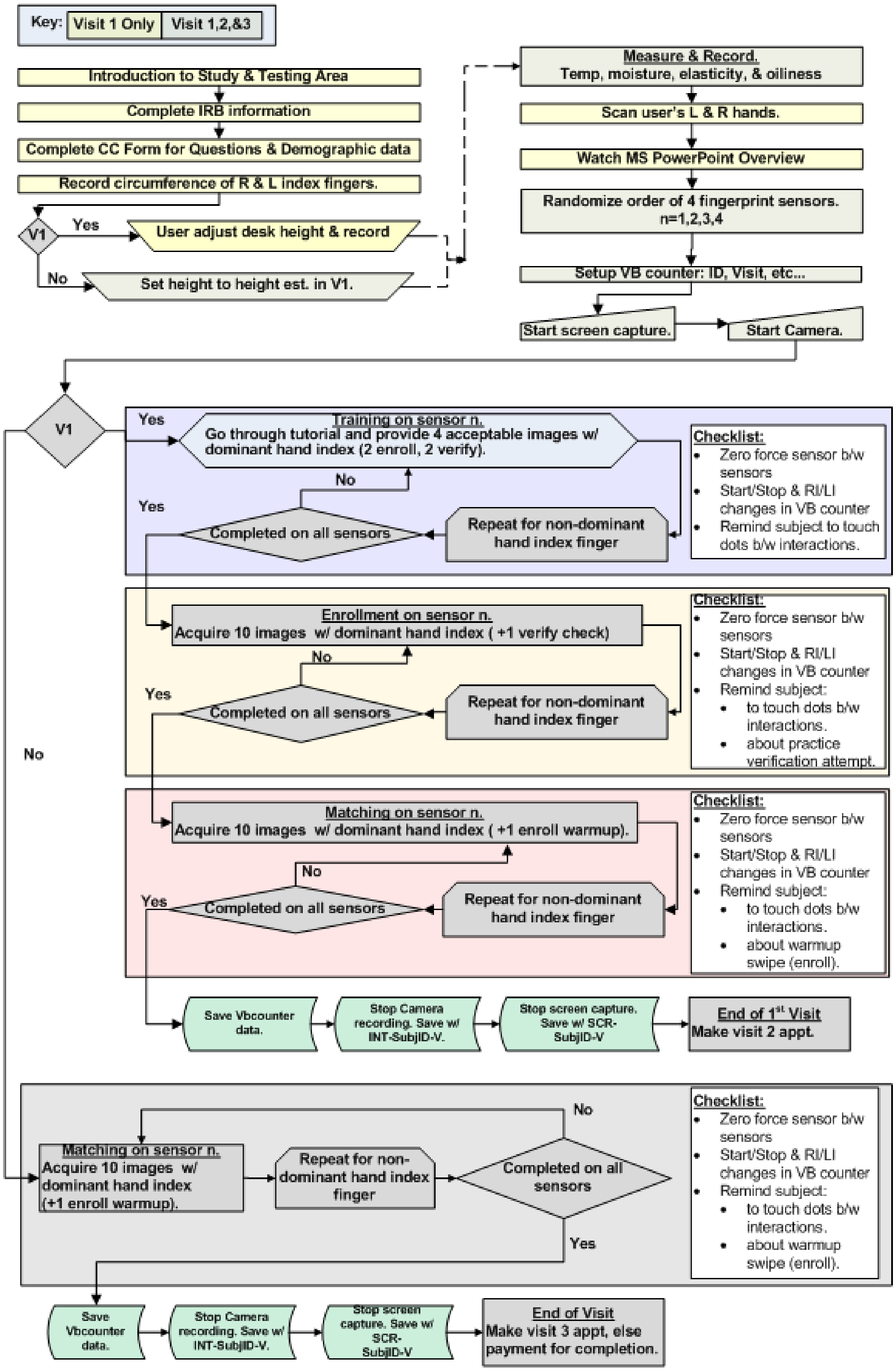
Questions?

If you do, please ask. If not, we will move onto training.

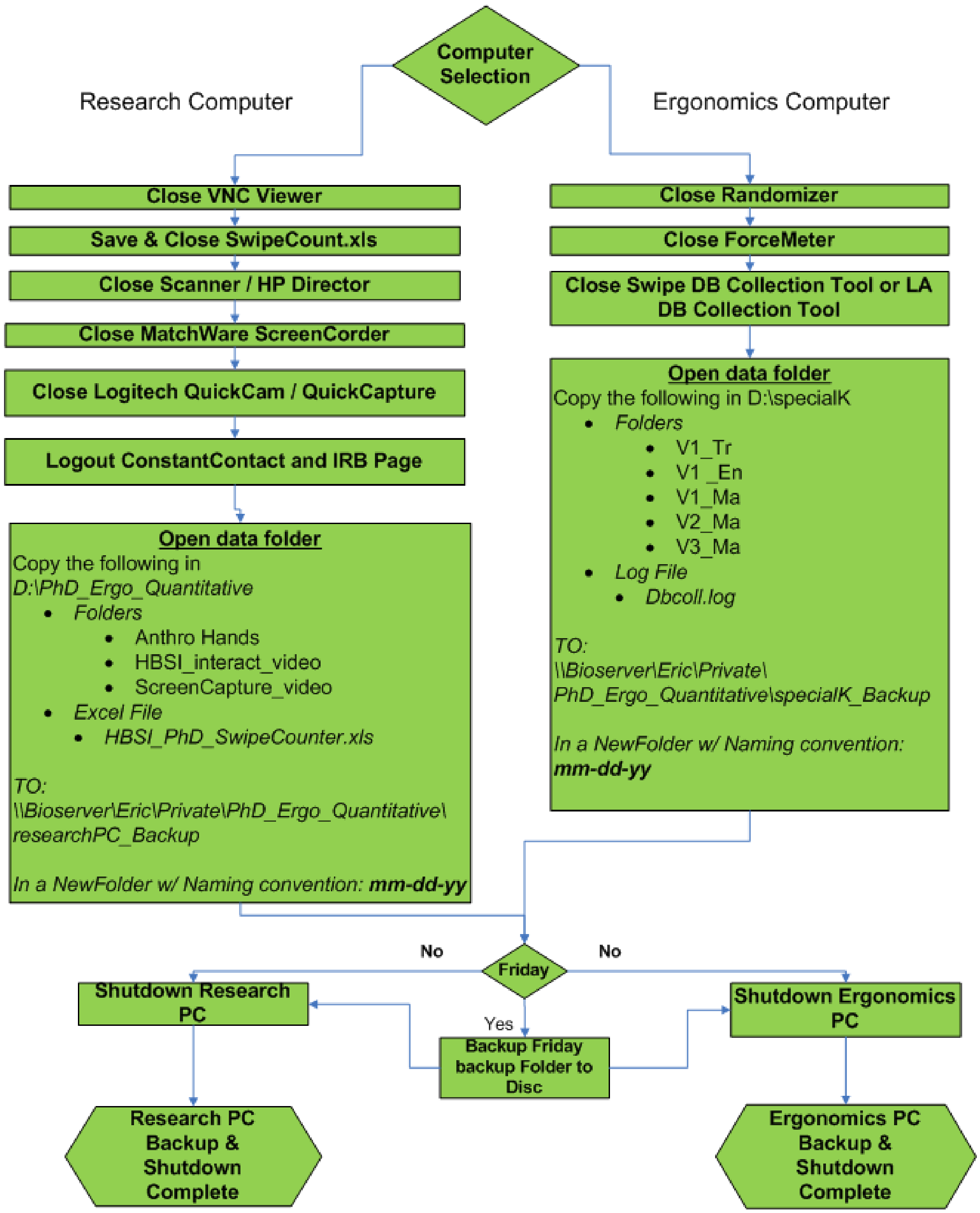
Appendix I. Data Collection Daily Startup Procedure



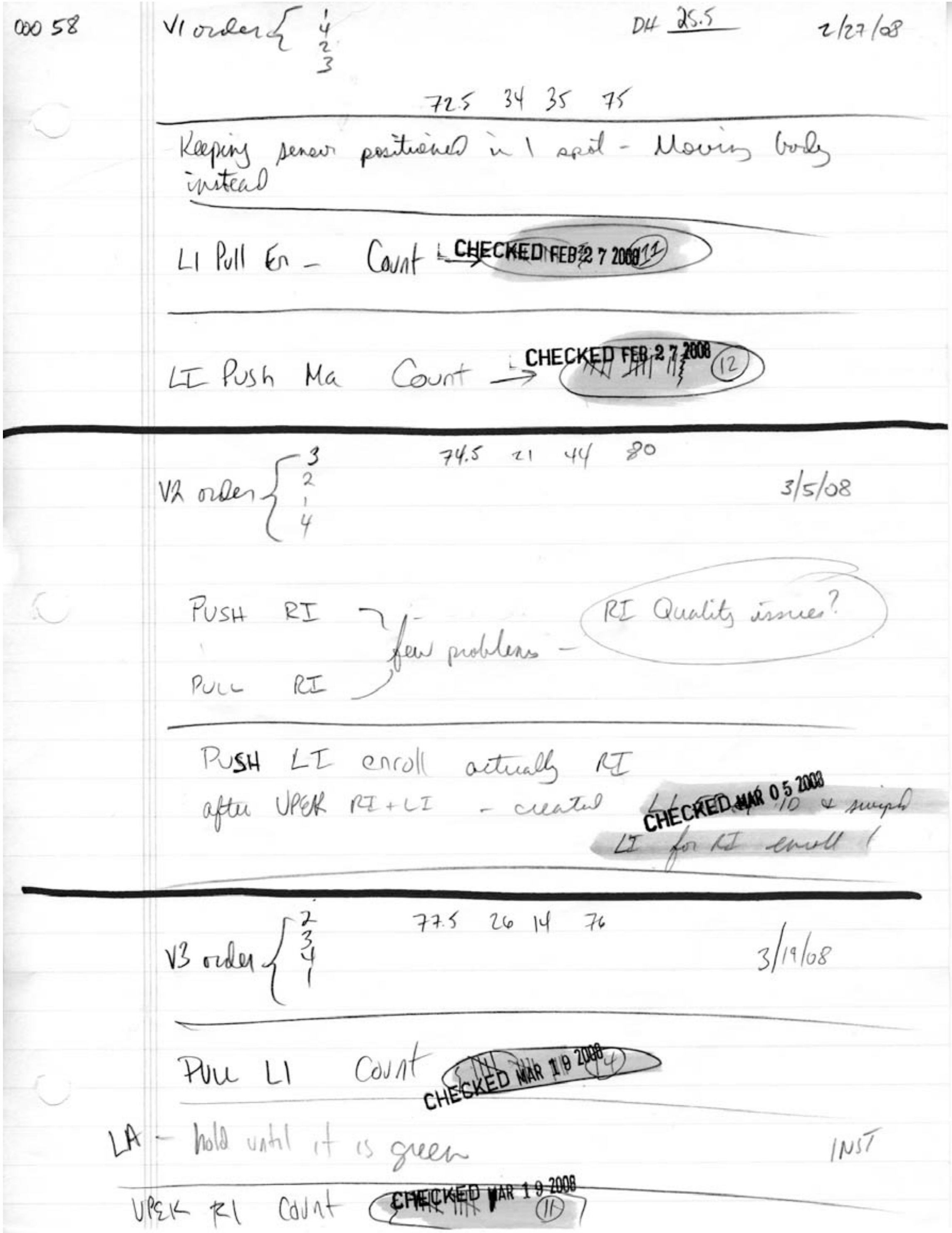
Appendix J. HBSI Data Collection Process



Appendix K. Daily/Weekly Backup and Shutdown Process



Appendix L. Example quantitative data collection participant observation document



000 58

V1 order { 1 4 2 3

DH 25.5

2/27/08

72.5 34 35 75

Keeping sensor positioned in 1 spot - Moving body instead

LI Pull En - Count CHECKED FEB 2 7 2008 (11)

LI Push Ma Count → CHECKED FEB 2 7 2008 (12)

V2 order { 3 2 1 4

74.5 21 44 80

3/5/08

PUSH RI } few problems - RI Quality issues?

PULL RI

PUSH LI enroll actually RI after UPEK RI + LI - created CHECKED MAR 0 5 2008 10 & swiped LI for RI enroll !

V3 order { 2 3 4 1

77.5 26 14 76

3/19/08

Pull LI Count CHECKED MAR 1 9 2008 (4)

LA - hold until it is green

INST

UPEK RI Count CHECKED MAR 1 9 2008 (11)

Appendix M. Demographic and Pre-Visit Surveys

HBSI

BSPALab > HBSI > HBSI_V1_Survey > Respond to this Survey

HBSI_V1_Survey: Respond to this Survey

* indicates a required field

1. ID (Provided by Test Administrator): *

2. Dominant Hand *

- Left
- Right
- Ambidexterous

3. Do you use hand moisturizer daily? *

- Yes
- No

4. Ethnicity *

- American Indian or Alaska Native
- Asian or Pacific Islander
- Black
- Hispanic / Latino
- White
- Other
- Specify your own value:

5. Do you have a musculoskeletal disorder (MSD) that affects your hands or fingers, such as arthritis, carpal tunnel syndrome, etc...? *

- No
- Yes, and please state the name.
- Specify your own value:

6. Please select one of the headings below that best describes your occupation. *

- Administrative, Business, Legal, Education, Sales, Computer Occupations
- Healthcare Practitioners and Technician Occupations
- Agriculture

- Construction, Installation, Maintenance, Production, Transportation
- Art/Design
- Food Preparation and Service
- Engineering, Life, or Physical Sciences
- Military and Protective Services
- I am a full time student and do not work
- Other
- Specify your own value:

7. Have you used fingerprint recognition devices before this study? *

- Yes
- No

8. What type of Fingerprint Recognition devices have you used? Please mark all that apply.

- Single finger glass or plastic device (optical)
- Multiple finger glass or plastic device (optical)
- Single finger metal / chip device (capacitance)
- Swipe-based fingerprint device
- Other
- Specify your own value:

9. Please make yourself comfortable with the test area. Adjust the desk height using the crank on the right side of the desk. Record Desk Height. *

10. RIGHT hand index finger circumference measurement *

11. LEFT hand index finger circumference measurement *

12. Dominant hand index finger temperature. *

13. Dominant hand index finger Moisture *

14. Dominant hand index finger Oiliness *

15. Dominant hand index finger Elasticity *

HBSI

BSPALab > HBSI > HBSI V2-3 > Respond to this Survey

HBSI V2-3: Respond to this Survey

* indicates a required field

1. ID (Provided by Test Administrator): *

2. Visit: *

- ◯ 2
- ◯ 3

3. Dominant hand index finger temperature *

4. Dominant hand index finger Moisture: *

5. Dominant hand index finger Oiliness *

6. Dominant hand index finger Elasticity: *

Appendix N. Quantitative Data Collection Equipment and Software

Computer Equipment:
- Dell Optiplex GX620 with Dual 17” monitors (Research Administrator Computer)
- Dell Optiplex 150, Single 17” monitor (DataCollection PC)
- TRENDnet 2-port KVM Switch TK-206i

Fingerprint Sensors:
1. UPEK Commercial form factor: Eikon 3C/42 1-way swipe
   SN - GBGB 0001635651
2. Push Design: Eikon 3C/42 DualSwipe SN - GBGB 000857633
3. Pull Design: Eikon 3C/42 1-way swipe SN - GBGB 0001640651
4. Large Area Commercial Sensor: UPEK TouchChip
   SN - ABAB0001082651

Sensors for Measuring Skin/Hand Characteristics:
- RayTek MiniTemp Infrared sensor (107811 RAYMT4U mfg: 7/18/2003)
- Moritex TripleSense (Model: K10229 SN:02618)
- HP ScanJet 4600

A/V Recording Equipment:
- Logitech QuickCam Notebook Deluxe Camera

Force Measurement Sensor:
- Vernier Force Plate

Software for Research Administrator PC
- Microsoft Internet Explorer 7.05730.11
- Microsoft Sharepoint / Constant Contact
- Internal IRB Database
- Flash Appointment
- RealVNC 4.1.2 (Build 5/12/2006 14:47:32)

- MatchWare ScreenCorder 4.0 (Build 65)
- Logitech QuickCam v11.5
- Microsoft Excel 2007
- HP Director

Software for Data Collection PC
- UPEK Internal DBCollection for format 381 native collection software 4.5.0.19
- UPEK TouchChip TPP DataBase Collection 1.1.0.0
- Vernier Logger Lite 1.3.2 Mar 18 2005 09:55:05 ISBN 1-929075-35-9
- RealVNC 4.1.2 (Build 5/12/2006 14:47:32)
- Microsoft PowerPoint 2007

Appendix O. Initial Coding Scheme for Fingerprint Recognition Users

1. Image Size
2. Ease of use
3. Form factor design
    a. Long Silver Swipe
        i. Likes
        ii. Dislikes
        iii. Swipe Problems
            1. Inconsistencies
            2. Software Usability
            3. Placement/Alignment
            4. Finger Support
            5. Physical Direction
            6. Sliding Surface
            7. Not Intuitive
            8. Form Factor
                a. Width
                b. Height off table
                c. Length
            9. Alignment
    b. Purple Round Swipe
        i. Likes
        ii. Dislikes
    c. Purple Square Swipe
        i. Likes
        ii. Dislikes
4. Changes/Suggestions
    a. Form Factor Size
        i. Width
        ii. Length
        iii. Height
    b. Slope
    c. Visual
    d. Tactile
    e. Physical Direction/Rotation
    f. Guidance
    g. Sliding Surface
    h. Sensor Position

Appendix P. Initial Coding Scheme for Non-Users

1. Image Size
2. Ease of use
3. Form factor design
    a. Long Silver Swipe
        i. Likes
        ii. Dislikes
        iii. No Instruction
            1. First Thoughts
            2. Process to Interact
        iv. Swipe Problems/Issues
            1. Inconsistencies
            2. Software Usability
            3. Placement/Alignment
            4. Finger Support
            5. Physical Direction
            6. Sliding Surface
            7. Not Intuitive
            8. Form Factor
                a. Width
                b. Height off table
                c. Length
                d. Hump
            9. Alignment
    b. Purple Round Swipe
        i. Likes
        ii. Dislikes
    c. Purple Square Swipe
        i. Likes
        ii. Dislikes
    d. Overall Preference
4. Changes/Suggestions
    a. Form Factor Size
        i. Width
        ii. Length
        iii. Height
        iv. Hump
    b. Slope
    c. Visual
    d. Tactile
    e. Physical Direction/Rotation
    f. Guidance
    g. Sliding Surface
    h. Sensor Position

Appendix Q. Initial Coding Scheme for Ergonomic Experts

1. Image Size
2. Ease of use
3. Form factor design
    a. Long Silver Swipe
        i. Likes
        ii. Dislikes
        iii. No Instruction
            1. First Thoughts
            2. Process to Interact
        iv. Swipe Problems/Issues
            1. Inconsistencies
            2. Software Usability
            3. Placement/Alignment
            4. Finger Support
            5. Physical Direction
            6. Sliding Surface
            7. Not Intuitive
            8. Form Factor
                a. Width
                b. Height off table
                c. Length
                d. Hump
            9. Alignment
    b. Purple Round Swipe
        i. Likes
        ii. Dislikes
    c. Purple Square Swipe
        i. Likes
        ii. Dislikes
    d. Overall Preference
4. Changes/Suggestions
    a. Form Factor Size
        i. Width
        ii. Length
        iii. Height
        iv. Hump
    b. Slope
    c. Visual
    d. Tactile
    e. Physical Direction/Rotation
    f. Guidance
    g. Sliding Surface
    h. Sensor Position

Appendix R. Qualitative Data Analysis

Table 129 Qualitative data results from interviews sorted by final design category.

Design Category	Subject [Line #]	Text from interviews
Sensor Design		
Shape		
Groove		
Movement		
Visual	001 [4927-5075]	Where as this one doesn't leave you much room for error. You really have to be looking at this one to use it. [in reference to purple square device]
	004 [3774-4062]	Maybe a picture up here or something. Like saying put your finger here and then with and arrow down or something. This one doesn’t have the arrows like the other one[newer sensor] did. [She pointed to the area above the sensor, where she felt she should start her swipe.](video 5:05-5:25)
	021 [11239-11649]	And so this definitely something like this [finger guide/impression] you are going to have to give some indication of once they are nicely positioned here they don't just stay there. Because I could see myself just leaving my finger there. And it almost reminds me of those medical devices, where they do the heart rhythm thing. It is almost like they are going to clamp it on and I'm just going to stay there.
	022 [7550-7616]	Visual cues, yea the form might help [pointed to the round swipe].
	020 [4865-5137]	I would change the dotting structure or put an arrow or something. When I first looked at it, I was like ""what do the dots mean?"". To me that represents something. But that is the symbol, human factors side of it. So, other than that there isn't really anything special.
	030 [5695-5844]	I've noticed this one [long silver swipe] has little dots, I'm not sure what the dots, if that's some aspect of it to help pick up the fingerprints."

	020 [3339-3870]	(video 5:36-6) So like the dots are close here and then they get wider. To me, it would be, I was just thinking it was like that as you move back.. You move towards the wider space. But it would seem like I don't know whether I should be going towards the dot, dots getting smaller or back away from the dots getting wider. Just because there is a difference. If all the dots were equally spaced, I would assume that it was just for aesthetically pleasing ideas. But the different spacing makes me believe there is a reason for it.
	021 [9179-9426]	I would definitely still go with some visuals; some kind of arrows letting me know that there is going to be movement involved and what direction that movement needs to occur in. You know starting with the fingerprint at the top, but I don't know.
	021 [6463-7009]	(video 10:00-11:03) Well when I sat down I thought it was going to be a press thing. Because I'm looking at the bulls eye [blue dots on the black tray] I know it's a fingerprint thing. So I thought I would be able to do this. Simple arrows showing the movement that is expected. You know on the sides or something would help because it shows what you are doing. Or even to put instead of having a design here, have a fake fingerprint so that you know that you are starting there, the arrows would indicate that you are then going to have movement.
	004 [5559-5710]	{ADMIN: And that is why you said if you would maybe put a fingerprint and show which direction…} Yes, just to show on here what to do. Yea. (video 7:13-7:18)
	022 [4536-5265]	I like the dots, because it kind of indicates the direction I want to go in. {ADMIN: From the dots, how do you know this?} The spacing between the dots indicates that you are going to start from here and go in that direction. So the spacing between the dots helps. The blue dots did not help me at all. They didn't really help tell me whether I need to start from there after that, before that, so its not really helping not that much. The blue dots definitely did help me align. {ADMIN: And can you explain that.} (video 8:09-8:18) Well the blue dot, helped me align because I needed to start from the center. So I knew that I was not way off. So if I could just start from there, somewhere around there. So kind of helped me align.

	021 [13666-13988]	(video 18:47-19:26) I like that I definitely I know where you want me to start here [with round swipe]. This one [round swipe] I think maybe even more than this [long silver swipe] one would need some arrows. This one [long silver swipe] I think at some point you would figure out that you are wanting some sort of swoop.
	002 [766-936]	I think it was stripes, I think that was the easiest to use. [She is referring to the latest device that replaces the dots with the stripes indicating which way to swipe]
	020 [2570-3001]	(video 4:49-5:22) I like the bump things right here [pointing to the colored dots on the black tray of the silver swipe sensor]. I guess they are not raised. But the look of it. Maybe if they were.. It seems like they are getting smaller and then wider [referencing the dots on the tray of the form factor] but maybe an arrow defined within the dots that likes the way you... rather than going forward going back [swipe direction].
Tactile	033 [4005-4170]	(video 7:32-7:52) This [round swipe] aids me in swiping my finger. Better sense of where to start and stop and even where to move because of the way it is designed.
	033 [3567-3788]	(video 6:23-7:28) This [round swipe] it kind of gives you a sense where you start, which is nice. And again it guides your path by the indention. It gives you a bit of a limitation, so that is nice and it is more compact.
	011 [4347-4468]	The more square one here I think it would be a little harder to figure where the sensor was unless you were looking at it
	022 [7204-7406]	(video 11:43-11:53) This one [round swipe] would aid. This one [round swipe] and this [long silver swipe] seem to be good at aiding the swipe. This one [square swipe] doesn't seem to be very efficient.
	023 [5939-6142]	(video 9:50-10:15) I think they [interacting with square swipe] would hinder it just because not being able to really put my finger down here without looking and being sure that I do it in the right way.
	006 [6761-6851]	(video 10:45-) I think this device (round swipe) is kind of helpful to align your finger.
	023 [8389-8475]	(video 12:58-13:08) As in ridges on the side so I could use it without looking at it.

	011 [3334-3458]	I liked the tray feel. You didn't have to look and you knew where your hand was. You could feel the edges. (video 5:35-5:42)
	023 [6143-6219]	This one [round swipe] I think aids a little bit more because of the sides.
	020 [8213-8299]	I liked this one [long silver swipe] for the shaping of the finger, the concave feel.
	010 [1547-1660]	I think it is very easy because it has like a cave here. You can just follow the ? tracks here. (video 2:45-2:53)
	008 [4027-4297]	I do like that it is like putting your finger down a groove. Since the way it works you can almost feel the sides. But that is one of the problems with making it wider. Is that you wouldn't feel the sides of it and know that you were directing your finger the right way.
	022 [7204-7406]	(video 11:43-11:53) This one [round swipe] would aid. This one [round swipe] and this [long silver swipe] seem to be good at aiding the swipe. This one [square swipe] doesn't seem to be very efficient.
	009 [5218-5357]	Personal preference I like this one (round swipe) more because it gives me more of a guide as to where to place your finger for the swipe.
	020 [4033-4117]	I liked the concave part here [pointing to grooves in the sensor] (video 6:22-6:26).
	001 [4239-4544]	(video 2:40) For this part here to give more leeway to kind of swipe it a little bit to the side and still work fine. Where as if you did it a little bit off and not in the center of the picture and if you did it real quick over and over it is really hard to get it in the same spot every time [alignment]
	033 [1941-2296]	(video 3:54-4:18) Well I like the design. It feels a little bit better because of the curvature, the use of it. Probably less likely to flick at the end as you described. It looks better, smaller, more compact. I also like that it gives you a better sense of where the path should be, specific with these lines [colored dots in lines on the channel] here.
	033 [3567-3788]	(video 6:23-7:28) This [round swipe] it kind of gives you a sense where you start, which is nice. And again it guides your path by the indention. It gives you a bit

		of a limitation, so that is nice and it is more compact.
	030 [4419-4776]	It [round swipe] does provide more of a cradle for the finger. And because my finger is shorter as I mentioned earlier it feels a bit more comfortable. I feel like I'm getting more of a... if i were to have to use this in a required setting I feel that it would take easier for me, because this [long silver swipe] one might be for more of a longer finger.
	032 [3478-3697]	(video 7:22-8) This one [square swipe] is a little too wide. I might tend to slide to one side or another. Again trying to just put my fingers on there I have to spread my fingers apart too far. So this one is too wide.
	009 [6214-6571]	(video 9:28-9:45) Again, its almost like you can pretty much [places finger and locks in round swipe]?. Where as with this being open yea you could, but you can still [rotates finger in square swipe] ? To me if I'm in a quick hurry and I'm just trying to swipe it I'd be more apt to have a rotation. Again depending on how sensitive the software would be."
	011 [4522-4663]	(video 7:43-7:53) Um I think this one again could be another design that could be useful just because you are stuck in there and I like that.
	020 [7989-8077]	I liked the finger thing there [the finger groove on the round swipe](video 12:30-12:33)
	006 [6996-7062]	So maybe a guide to align your finger better would be a good idea.
	009 [6888-7390]	(video 10:10-10:41) I do like that because it is much more at least the edges are much closer so I don't tend to have that. Where as here I am going to have a little more play. Again that though, qualify that I mean the software is fairly sensitive where you need to make sure the you have kind of is the same finger position for the most part then that to me would be an issue. And I guess from a security standpoint I'd hope it be fairly sensitive so Joe Schmo couldn't come up and get into my stuff.

	021 [12645-12896]	(video 17:13-17:26) With this one [square swipe], I think I might leave it as is, and just re-position my finger, which I think would cause you a problem. Because there are no guides at all for where to put the finger. Still the upward slope is good."
	006 [6852-6995]	And this one (square swipe), ugh is not too helpful, its purpose of the depth is because its wants you to align but is not as good as this one.
	014 [4707-4887]	[square swipe] (video 7:15-7:28) This there is so much surface area and there is not a.. I guess you could miss the target zone by a little bit and it would throw off your reading.
	002 [6557-7066]	Here you have to take care if you were going on this surface and if your finger was smaller which mine is it was making problem with this one. I have to be really in the middle with this one I didn't have any problem because its covered[swipe carefully to make sure it is centered][striped sensor has a smaller sensor]. I think when it was the smaller one I had problems. If I was going right to here or right to there. (video 7:08-7:38). {ADMIN: Okay, so if you were off-centered you had some problems?} Yes.
	030 [5589-5668]	(video 10:37-10:57) Well what I like is the raised sides [on the round swipe].
	030 [4419-4776]	It [round swipe] does provide more of a cradle for the finger. And because my finger is shorter as I mentioned earlier it feels a bit more comfortable. I feel like I'm getting more of a... if i were to have to use this in a required setting I feel that it would take easier for me, because this [long silver swipe] one might be for more of a longer finger.
	023 [8180-8354]	Or like something that would be guided on either side of my fingers. For design purposes you couldn't make it too tight, but I would design this so it is more guided as well.
	004 [7829-7968]	But I mean this one [round purple sensor] seems a bit easier because it has the impression of a finger. So this ones a little more clear .
	005 [5185-5481]	(video 7:31-8:12) I guess to me it wouldn't really matter just because .. Well it [guide impression on round swipe] would keep your finger in there. I mean that is okay, but I would make this flat here. This one [square swipe] I don't know if I have a

		recommendation just because I don't like it.
	011 [4522-4663]	(video 7:43-7:53) Um I think this one again could be another design that could be useful just because you are stuck in there and I like that.
	011 [4213-4346]	This one [round swipe] seems okay because again you have something to reference where you are without having to look at it and focus.
	014 [4472-4702]	[round swipe] (video 7-7:15) I like this one really nicely because it's easy? It's easy you know exactly where your finger is going to go, and you can just guide it in there. From a tactile standpoint, it makes it very, very easy.
	009 [3337-3605]	that's not concave, that is the other way, but anyway. But if it was just more of a shape to it as opposed to a .. that might make it person that might make it a little bit easier because it would be more consistent in placing the finger without the rolling of the hand
	009 [5358-5444]	This (square swipe) seems to be more open so you could have more rotation in the hand.
	012 [2966-3035]	Like this [round swipe] has the finger so I would think it goes out.
	030 [4777-4887]	This one [square swipe] I don't know. It doesn't have anything to cradle the finger. I'm sure it's functional.
Depth	030 [2989-3077]	Other than a deeper cradle would feel more comfortable I believe. I think it would aid.
	002 [7753-7887]	I don't know, this is kind of weird, too much material for that (video 8:58-9:01) [pointing to the guidance on the round swipe sensor]
	032 [4642-4811]	(video 9:07-9:38) The only thing I would probably do to this one [long silver swipe] is maybe raise the outside/exterior walls, the side walls, just a bit, not too much.

	021 [14827-15192]	As far as the design I actually think I would do something in between the two [round swipe and long silver swipe] as far as the sides go, the ridges here. This one [long silver swipe] doesn't quite keep me channeled enough. This one [round swipe] is almost too locked in and discourages me from movement. So actually I think I would do something in between the two.
	030 [2607-2738]	I don't know if it would be beneficial to have the cradle your finger a little more so that it rests a little more into the device.
	009 [3026-3607]	(video 5:10-5:43) Um, no I wouldn't necessarily say that it hindered. I think if and I realize people's fingers are a little bit different. But if it was.. It just seemed like there was a lot of room to kind of rotate the finger and instead. I don't know if that would create errors where as if it were more .. that's not concave, that is the other way, but anyway. But if it was just more of a shape to it as opposed to a .. that might make it person that might make it a little bit easier because it would be more consistent in placing the finger without the rolling of the hand.
	023 [5092-5849]	There is room for error a little bit in this one [long silver swipe], but in this [touching square swipe] I have to be more precise in how I do it to cover the window. And this one [long silver swipe], I guess one thing I notice now that I see these [square swipe] is that it sort of has guards on the sides that keep you from going over and these [square swipe] there is not as much of like a set definition of okay your goes here so you cannot do it easily without looking. Where as this one [silver long swipe] without looking I can do it fairly easily. And this [round swipe] kind of can, but I don't know why it doesn't come down [referencing the guide impression and why it is missing on the sides next to the sensor] so my finger can go over it more.
	021 [4904-5011]	But I would still say some ridges that hold my finger in a little bit more [guide to align tip of finger].
	020 [8894-9116]	(video 13:41-14) If I was redesigning this one [long silver swipe] I would add something to this element. And maybe even up the sides a little more, but not too much to where people with wider fingers could not access it.

	014 [2649-2907]	(video 4:17-4:35) I guess the only change would be if you have to use your thumb print on an ongoing basis maybe a little bit more of an angled side [channel or tray for the finger]. But for just using either your index or middle finger it worked very well.
	030 [3821-3991]	(video 8:07-8:15) I would probably just try to change the depth of the cradle like I said the curve of it, a little bit, just because it would be more comfortable to me.
Start/Stop Position		
Visual	001 [5460-5594]	It looks like this is where you are supposed to put the tip of your finger right here [pointing to purple round ""groove"" for finger]
	021 [11684-11739]	The guiding the finger with the starting point is good.
	031 [6752-7264]	(video 11-11:33) This one [square swipe] isn't bad. If this black would always be on there [informed participant, black tape is just covering device name and that it would not be on there]. Okay, that black tape kind of tells me to stop there. But in that case [knowing it shouldn't be there], it is okay, it is better than the first one [long silver swipe] I felt, but I would probably go to far with it too. But I feel like... It is at least more comfortable than the longer one. So the shorter size is better.
	021 [6463-7009]	(video 10:00-11:03) Well when I sat down I thought it was going to be a press thing. Because I'm looking at the bulls eye [blue dots on the black tray] I know it's a fingerprint thing. So I thought I would be able to do this. Simple arrows showing the movement that is expected. You know on the sides or something would help because it shows what you are doing. Or even to put instead of having a design here, have a fake fingerprint so that you know that you are starting there, the arrows would indicate that you are then going to have movement.
	022 [6674-6792]	(video 11:05-11:10) [round swipe] The one in the middle seems to have a good starting position. I knew where to start.
	022 [8304-8531]	Assuming we are doing a swipe, I would suggest doing a rectangular shaped device [pointed to long silver swipe] would be definitely better, because it

		generates the idea you have to do a swipe. A starting point is much helpful.
	033 [1941-2296]	(video 3:54-4:18) Well I like the design. It feels a little bit better because of the curvature, the use of it. Probably less likely to flick at the end as you described. It looks better, smaller, more compact. I also like that it gives you a better sense of where the path should be, specific with these lines [colored dots in lines on the channel] here.
	001 [5816-6012]	I guess the most convenient thing would be to have a design like this [pointed to round purple device] (video 3:40) where it is very obvious where to put your finger and where to begin your swipe.
	004 [5299-5710]	(video 6:54-7:07) Yea, You really don't know what to do.. If you are supposed to go like this [swipes entire finger correctly, places finger on sensor], or you know .. If you don't know what to do. If someone just walked up and said take your fingerprint.. {ADMIN: And that is why you said if you would maybe put a fingerprint and show which direction…} Yes, just to show on here what to do. Yea. (video 7:13-7:18)
	033 [4005-4170]	(video 7:32-7:52) This [round swipe] aids me in swiping my finger. Better sense of where to start and stop and even where to move because of the way it is designed.
	021 [9881-10372]	(video 14:09-14:37) Well and again with these kind of dots you will have a lot of people that don't even notice them. So if they are important they need to be more obvious. Because the lighting in here is very good, and I have good eyes. Other people would maybe not even see that. And especially a lot of guys do not differentiate between color as much. And definitely if you are color blind you are going to have a real problem with this, assuming the blue is trying to tell you something.
	003 [1581-1750]	Yea I had to figure out where to place my finger like I have small hands so if I started at the very end it registered better than just a quick swipe. (video 2:39-3:00)
	008 [5828-6085]	(video 7:22-7:50)Actually I am assuming that well there is this blue part that I think is an indicator of where you are supposed to put your finger but it wasn't really clear which part of your finger starts there. But again that is something I think you would

		read in the instructions then it would be obvious.
	031 [5650-5987]	(video 9:36-10:03) This one [round swipe] I like best mainly because it gives you the end where your finger needs to be. So I kind of like the fact that is there, it lets you know not to go too far back with your finger. And even though it does sit up a little bit higher in the back, because it is shorter, it is more comfortable to me.
	033 [2611-2966]	(video 4:49-5:30) One thing that I don't think most people would not know necessarily is to where to start and stop. You know, do you put your full finger on here? Or is the intention to get a swipe of the whole finger? There might be a way to put some kind of a visual aid to let people know where to start with the specific digit, location of the digit.
	020 [7294-7845]	(video 11:41-12:22) But this one [round swipe] you have the finger shape even. It shows you what you need to do. However this one for people with larger fingers I just happen to have short fat fingers so it happens to work well for me. But someone with longer fingers or wide fingers, I mean that kind of constricts. But at least it tells you.... I mean if someone tells you ""this is a fingerprint sensor"" I would at least be able to know my finger goes there [correctly places finger on round swipe]. I mean that kind of cue of the curviness helps.
	022 [4536-5265]	I like the dots, because it kind of indicates the direction I want to go in. {ADMIN: From the dots, how do you know this?} The spacing between the dots indicates that you are going to start from here and go in that direction. So the spacing between the dots helps. The blue dots did not help me at all. They didn't really help tell me whether I need to start from there after that, before that, so its not really helping not that much. The blue dots definitely did help me align. {ADMIN: And can you explain that.} (video 8:09-8:18) Well the blue dot, helped me align because I needed to start from the center. So I knew that I was not way off. So if I could just start from there, somewhere around there. So kind of helped me align.

	004 [3774-4062]	Maybe a picture up here or something. Like saying put your finger here and then with and arrow down or something. This one doesn't have the arrows like the other one[newer sensor] did. [She pointed to the area above the sensor, where she felt she should start her swipe.](video 5:05-5:25)
	021 [13666-13988]	(video 18:47-19:26) I like that I definitely I know where you want me to start here [with round swipe]. This one [round swipe] I think maybe even more than this [long silver swipe] one would need some arrows. This one [long silver swipe] I think at some point you would figure out that you are wanting some sort of swoop.
	020 [5645-5920]	(video 9:06-9:36) [discusses round swipe] This one I like though. This one is interesting because it targets you on where, how far you need to place your finger in. And it doesn't with that hump there, before I was feeling like I had to press down. That it is just a gradual.
Tactile	006 [6761-6851]	(video 10:45-) I think this device (round swipe) is kind of helpful to align your finger.
	020 [5711-5809]	This one is interesting because it targets you on where, how far you need to place your finger in.
	032 [4009-4277]	(video 8:13-8:55) This one [square swipe] I don't like at all. I don't know what it is about it this one, but I don't like it. This one [round swipe] the stopper up front is kind of nice and the walls to the side, so I am restricted to be in that zone. Those are okay.
	020 [8143-8212]	(video 12:43-13:08) I liked this one [round swipe] for the placement.
	013 [6946-7401]	(video 9:57-10:45) [referencing the round swipe] It is just easier. I think it gives you a better place to put the finger. It is easier to control factor for lack of better word. This one [long silver swipe] as I said but going across the sensor is a lot smoother. Maybe adjust it because I don't know as I said those are sticking up. But the design of it [round swipe], I like better, the going across the sensor I like better here [long silver swipe]."
	011 [4128-4347]	(video 6:58-7:25) I don't like the square one here, I assume this is another swipe. This one [round swipe] seems okay because again you have something to

		reference where you are without having to look at it and focus.
	007 [3232-3320]	(video 4:22 - 4:36) I like how this one [round swipe] kind of lines up your finger first
	033 [3567-3788]	(video 6:23-7:28) This [round swipe] it kind of gives you a sense where you start, which is nice. And again it guides your path by the indention. It gives you a bit of a limitation, so that is nice and it is more compact.
	032 [2781-2938]	Yea don't like that [square swipe]. Yea I don't like this one [square swipe]. It [square swipe] has too many variants, gradients. It is too wide for me.
	004 [7427-7968]	(video 9:57-10:35) This one [points to long silver swipe] umm well I know I would imagine it is like this [places finger on round purple swipe correctly w/o training]. Umm this one you don't really know if you just put your finger here or its not really clear if it's a swipe [interacts with the long silver swipe sensor]. I mean I know it's a swipe so its hard to say I don't know what to do with it. But I mean this one [round purple sensor] seems a bit easier because it has the impression of a finger. So this ones a little more clear .
	009 [6214-6571]	(video 9:28-9:45) Again, its almost like you can pretty much [places finger and locks in round swipe]?. Where as with this being open yea you could, but you can still [rotates finger in square swipe] ? To me if I'm in a quick hurry and I'm just trying to swipe it I'd be more apt to have a rotation. Again depending on how sensitive the software would be."
	009 [5192-5358]	(video 7:52-8:40) Likes?. Personal preference I like this one (round swipe) more because it gives me more of a guide as to where to place your finger for the swipe.
	014 [4472-4702]	[round swipe] (video 7-7:15) I like this one really nicely because it's easy? It's easy you know exactly where your finger is going to go, and you can just guide it in there. From a tactile standpoint, it makes it very, very easy.
	001 [6068-6159]	most of my inconsistencies came from was where I was starting my swipe in a different place

	021 [11684-11739]	The guiding the finger with the starting point is good.
	020 [8721-8811]	(video 13:30-13:34) I would put some sort of curved thing on this one [long silver swipe].
	030 [6187-6356]	If this part [round swipe finger guide] could be incorporated into this [long silver swipe] to cradle my finger I probably would like this one better than any of them.
	031 [6194-6694]	(video 10:25-10:55) It aided [pointing to round swipe]. I liked it. I like the fact that it [round swipe] had the design to guide your finger right where to put it. Instead of having to kind of figure.. I think the very first one [long silver swipe] you would think especially with the little blue dots you would have to be getting in that area. That is longer. I like the shorter, if it is just for fingerprint, I like the shorter one. And I like the fact that it tells you where to put your finger.
	009 [1984-2307]	(video 3:10-3:30) Initially, I would kind actually take and extend past that so I kind of put the sensor behind it and then I would swipe for my initial verification. When I went back to verify it doing the same thing it wouldn't read it. But if I kind of aligned and just did the simple fingertip it seemed to accept it."
	007 [3232-3609]	(video 4:22 - 4:36) I like how this one [round swipe] kind of lines up your finger first, and this one [square swipe] doesn't do anything at all. So maybe you put this little thing right here [points to the alignment finger impression on the round swipe] to line it up, it is probably better than just that blue spot [points to the silver long swipe blue area above the chip]."
	022 [3841-4439]	(video 6:42-7:10) But after I get this message I only know I need to use this device. That is the message alerting me that. However, once I put my finger here I wouldn't know when to start. Lets say using this function I could place my finger 1cm behind or ahead. Maybe that isn't the right way to go about it. So if there was some sort of depression or an endpoint that would indicate the user is in the right position and can start now, even though the data is actually been recording for the full time. I was thinking maybe a depression or a click, something of that, to let the person know.

	022 [2653-3522]	(video 4:42-5:56) I would say definitely aids, however I don't know when to start. Think of a mouse, I know when I click it, it is going to happen. As with here, I don't know where to start. So there has to be some impetus that the person. Okay, the person needs to know now that it is capturing. As a programmer you know that this is going to capture all the time and it is.. However the person needs to know I am in the right spot and it can start taking the fingerprint now. So if you can have some sort of click mechanism here saying that if you've pressed it. It may not actually do anything, but for the person to know that I am in the right position and it can start taking data now. There can probably be some sort of click function or some sort of depression that goes down. Now that you are here you can start doing. So the person themself knows its intuitive
	032 [3015-3268]	This one [round swipe], it actually for the length of my fingers, the front little hump kind of stops you from going comfortably further along, you just kind of run into it. I guess that is supposed to be to show you where to stop. That would be enough.
	004 [7829-7965]	But I mean this one [round purple sensor] seems a bit easier because it has the impression of a finger. So this ones a little more clear
	031 [5650-5987]	(video 9:36-10:03) This one [round swipe] I like best mainly because it gives you the end where your finger needs to be. So I kind of like the fact that is there, it lets you know not to go too far back with your finger. And even though it does sit up a little bit higher in the back, because it is shorter, it is more comfortable to me.
	021 [6072-6300]	I'm thinking some kind of tiny little ridge at the end [top of the sensor by the cable] might actually help me some so I don't overshoot, or does that even matter? If I start too high up as long as I make contact does it matter?
Smooth	010 [3359-3419]	This, I think this [long silver swipe] feels more smoothly.
	010 [2301-2379]	Yea I like the shape. Its very smoothly to swipe your hand. (video 4:30-4:35)

Raised Sensor	020 [4118-4306]	I like how this is raised a little bit [the actual capacitance sensor], so you do feel as you are going over it the sensor aspect. I mean that is nice how that is raised. (video 6:37-6:53)
	022 [6479-6669]	With respect to this one [square swipe], there might be a lost of contact because of the depression. So if I were to keep my finger just on top of this it maybe would not capture the data. "
	003 [5707-5778]	I like the swipe because you can feel where it is crossing your finger
	003 [4539-5082]	I think with this one, because you have the little bars there that you can actually know when you're done crossing it that it actually has read it. I am not sure if that part there is the reader or if it is the whole thing. {ADMIN: The actual sensor is just the middle part.} Yea that is what I thought. Because you can run your whole finger across and you it feels like you have the knowledge that it read it. (video 6:26-6:32) Where if there isn't anything on the others and you just have a space but you don't know exactly where it is reading.
	002 [8448-8719]	Yes, I was thinking like should it be this wide? Yea, those are smaller. (video 9:50-10:00) [silver is wide, purple sensors are smaller -- she pointed to them]This didn't feel so comfortable because you have those two. And each time you go over it you have to go over it.
Angle Position - Roll	006 [6161-6550]	(video 9:45-10:18) It would be hard to say. I think the way they designed it was because they can use two hands. Because if I design it sideways you would use it for one hand and you would have to turn it the other way to start the other. So, either they find a way to flip the sensor around depending on the sensor [rotate like a lever for both hands] or have a mirror for the other side.
	021 [4212-4474]	(video 6:12-7:18) I still would want it off to the side, because I'm still coming at an angle [hand/arm angled - when shoulders are square with the desk she would prefer device angled - imagine right hand straight out, rotate hand to the left towards the thumb].

	021 [7851-8587]	For right handedness I would actually say to some extent you are coming in at a slight angle because your pinky finger is going to lean downward as you work on this device. Makes me wonder if it [the swipe sensor] should be at a slight angle. So that you get full contact with the finger. I'm thinking the way I would actually use it, I'm coming off to the right, to a right angle. It almost seems like it needs to be ramped if I really need good coverage across that. I mean it could be that if I could drag it real quickly then it's not important. But if I am having a problem making enough contact, I think a slight ramping off to the right side would help. But of course that will totally screw up someone that is left handed.
Angle Position - Yaw	008 [2874-2973]	if it was fastened to anything I would say maybe have it on a little post so it could be swiveled.
	006 [3539-3915]	(video 6:03-6:16) It was more comfortable and it was more precise in my opinion because I was noticing when I was swiping like this [as instructed] sometimes it didn't get all my finger [illustrates to me the finger pad of the index finger] it had some spots that was missing. So, when I swipe it like this [sensor rotated about 90 degrees], it was grabbing all of my finger.
	021 [12466-12641]	(video 17:03-17:12) For this one [round swipe] I would feel like I wanted to position it. I know I can tell which way my finger should be going so I would want it positioned.
	003 [3486-3866]	(video 5:10-5:35) Probably more hindering, because if you had it stable you would have to constantly figure out how you are going .. Because if you don't have it straight it doesn't read it right. {ADMIN: Oh, your finger on the sensor?} So if it is this way [sensor perpendicular to your shoulders] (video 5:27-5:35) you really have to angle your body if you cannot move it around.
Slope		
Flat	031 [3626-3879]	I'm thinking if you were swiping this way [turned device around](video 6:30-6:35) where you are coming up, you feel like you are having to position your wrist I don't know it just doesn't feel as comfortable to me as maybe if it were flat, totally flat.

	031 [7806-8052]	(video 12:28-13:01) The design I like about it [square swipe] is like the size, it is a little bit smaller. And even though the back of it is a little higher up, it is more even, than to go from a lower front to a higher back [long silver swipe].
	031 [4725-5113]	And so make it a little bit smaller and flat and not make it come up in the end, even though that maybe makes it ""ergonomically correct"", I don't know. Because I think it makes you, it drags, I just don't like the way that does. I feel like I'm catching myself. I just think if it was flat [turns device around to utilize the flat part of the sensor], it seems like it be much [better]
No Hump	031 [2550-2900]	I don't know if I like that part, the part that comes up at the end [the hump at the end opposite the cable]. It just feels like I'm up really high, because that is when I start to drag my nail, so if my nails were done or something, I think it would be an issue. I think I would pull up and do that, just because I have these short hands or fingers.
	031 [4532-4724]	(video 7:35-8:20) In this is because of my size of hand and fingers I think it could be smaller and I think you could still get the same purpose out of it, if the whole back area wasn't there.
	020 [2051-2473]	(video 3:38-4:40) I feel like with this hump here that it causes me to kind of want to do the "flicking" thing [shown in the training video]. I feel like it has lifted my finger too high. So I feel like I have to press and almost push this up in a sense to get it to where it would scan, mentally. I don't know if it would still capture just going across. I feel like I would need to press that part down to go across.
	031 [3309-3609]	(video 6:07-6:45) I think once you got comfortable, maybe if this back part, I don't know maybe it doesn't need to be as long, the whole device. And I guess this whole back part, if this serves no purpose here but to sit it up, I guess it would be more comfortable to use, because you wouldn't have.
	031 [4041-4321]	(video 7:04-7:29) One thing that I don't like. It seems fine and that it would work fine except for I think it is either too long or I don't think you need the back little bump on it that brings, it is almost like a rest. I don't think you need the rest part -the back rest on it.
	020 [4307-4525]	I don't like how this [the end opposite to the cable] is such a big hump that it like kind of lifts your finger to the sense that when you are pulling across you feel

		like you have to press the tip of your finger down.
Down	033 [1941-2296]	(video 3:54-4:18) Well I like the design. It feels a little bit better because of the curvature, the use of it. Probably less likely to flick at the end as you described. It looks better, smaller, more compact. I also like that it gives you a better sense of where the path should be, specific with these lines [colored dots in lines on the channel] here.
	032 [1893-2067]	(video 3:57-4:15) No, like I said I like the bulge or hump at the end because it does make your finger naturally go in the position that would cause it to swipe it correctly.
	005 [2928-3030]	(video 4:30-4:45) I thought it was pretty good. It was comfortable. It was just about the right angle.
	021 [11650-11683]	So the tilt going upward is good.
	032 [1537-1795]	(video 3:22-3:45) No, actually it helps because it almost naturally makes your finger go about as far forward as it should because of the hump. I can't do that, but I can do this. And it has that nice little dip so it guides your finger where it needs to go.
	012 [2167-2260]	I thought it aided because it has the slope raised up over here so that you can drag it off.
	021 [5665-5895]	(video 8:53-9:47) I think it works well. The nice upward slope works because as you are pulling your hand back your finger kind of has to get higher and the way that it is sloped higher towards the end of the swipe is appropriate.
	014 [2998-3251]	(video 4:48-5:18) I think it aided and I think especially the base of it and how it kind of rises up. It makes it easier to keep your finger level, on the sensor. It is more natural motion to kind of swipe up, as in when you are coming back towards you.
	009 [3781-4077]	It was very simple. It allowed for the natural curvature of the hand especially when you are using your fingers with it raised on the end you are able to still get your hand in there and work it. Again, the difficulty with the thumbs. I think that is just normal with the

		position. (video 6-6:10)
	020 [5645-5920]	(video 9:06-9:36) [discusses round swipe] This one I like though. This one is interesting because it targets you on where, how far you need to place your finger in. And it doesn't with that hump there, before I was feeling like I had to press down. That it is just a gradual.
	023 [7902-7992]	So I guess I would keep the sloping motion of that [hump on the back of long silver swipe]
	023 [3595-3708]	(video 6:18-6:53) I think I like the size and because it slopes up it makes it easier as you are sort of leaving.
	032 [2390-2629]	(video 4:35-5) No, I really wouldn't because it has that natural bend your finger would take anyway. As opposed to if it were just flat, you don't put your finger flat on anything. It is an awkward thing. But that it is really comfortable.
Flatter	020 [4307-4525]	I don't like how this [the end opposite to the cable] is such a big hump that it like kind of lifts your finger to the sense that when you are pulling across you feel like you have to press the tip of your finger down.
	020 [4659-4864]	(video 7:06-8:06) I think that if there was a little divot here [pointing to the area where the hump is] for the concaveness. I mean you can still have a little lift [hump] but it is just kind of dramatic.
	002 [4763-4859]	Yea, I would make this lower. (video 4:40-5) [referencing the back of the sensor that slopes up]
	031 [3309-3609]	(video 6:07-6:45) I think once you got comfortable, maybe if this back part, I don't know maybe it doesn't need to be as long, the whole device. And I guess this whole back part, if this serves no purpose here but to sit it up, I guess it would be more comfortable to use, because you wouldn't have.
	011 [3510-3555]	Aside from the angle I guess really nothing.

	011 [3764-3985]	Like I said I guess a little flatter maybe something raised in the front, I don't know if that would be easier or not. Especially with the thumb it was kind of hard to pull up and get a decent reading. (video 6:15-6:25)
	031 [3609-3881]	Because you have I'm thinking if you were swiping this way [turned device around](video 6:30-6:35) where you are coming up, you feel like you are having to position your wrist I don't know it just doesn't feel as comfortable to me as maybe if it were flat, totally flat."
	031 [8053-8146]	I feel like the first one has too much of an incline [long silver swipe] from front to back.
	020 [9116-9197]	And then I would flatten this [the hump at the end opposite the cable] out a bit.
Up	006 [2942-3098]	{ADMIN: So you would rather have it on an incline?} (video 5:13-5:26) yea, so it feels more natural to place your hand like this. Well actually yea like that.
	001 [3344-3436]	I mean like I would set it up like that [tilt upwards (1:54 in the video)] …. Just slightly
	008 [3094-3277]	Well pretty much how I held it was like this so we need to angle this way. So maybe if it was something if was on an angle so it could this way and go to the sides. (video 4:41-4:53)
	001 [3207-3299]	I would maybe make it go on something that was elevated. I would add an angle or something.
	002 [4685-5422]	Yea, I would make this lower. (video 4:40-5) [referencing the back of the sensor that slopes up]. {ADMIN: So, (pointing to the device), you would make this slope of the sensor lower?} Yes, lower because it is like this (video 4:50-5:03) [showing me that it forces her to lift up her finger before swipe is complete]. {ADMIN: So, it kind of makes you lift your finger up?} Yes. Like with this one it is not so comfortable (video 4:55-5:03). (video 5:04- 5:15) This is more comfortable….. Reverse… {ADMIN: So a downward slope?} Yes, like reverse, because my finger is going up. And here its… I don't know what's better but I guess this [slope] should be smaller. Yea.

	006 [2406-2756]	(video 4:32-5:05) Um, yes but I would have preferred it if it would have been like this [tilted up the sensor so the end with the USB cable is elevated off the table and the side with the logo is touching the table]. A little bit higher so it is easier to swipe. Because like this sometimes you have to place your hand higher than the sensor to move it.
Size		
Length		
Too Long (make shorter)	031 [7234-7264]	So the shorter size is better.
	031 [4041-4321]	(video 7:04-7:29) One thing that I don't like. It seems fine and that it would work fine except for I think it is either too long or I don't think you need the back little bump on it that brings, it is almost like a rest. I don't think you need the rest part -the back rest on it.
	031 [5317-5644]	(video 9-9:32) Maybe this being smaller, and being able to grab here, that is comfortable. Even though it sits higher because the whole thing really sits up well the backs a little bit higher, but it doesn't seem so bad maybe because of the length of it. [compares square swipe to long silver swipe to see difference in height]
	031 [7806-8052]	(video 12:28-13:01) The design I like about it [square swipe] is like the size, it is a little bit smaller. And even though the back of it is a little higher up, it is more even, than to go from a lower front to a higher back [long silver swipe].
	002 [9133-9359]	Hmm, maybe this is too long really, probably. (video 10:56 - 11:07)"
	031 [8693-8852]	if all you are needing is the tip of your finger, not the tip but the very first indent of the finger, it doesn't need to be a very long device I don't think.
	031 [4532-4724]	(video 7:35-8:20) In this is because of my size of hand and fingers I think it could be smaller and I think you could still get the same purpose out of it, if the whole back area wasn't there.
	031 [8146-8206]	So the size of the two purple ones are easier for me to use.

	031 [6752-7264]	(video 11-11:33) This one [square swipe] isn't bad. If this black would always be on there [informed participant, black tape is just covering device name and that it would not be on there]. Okay, that black tape kind of tells me to stop there. But in that case [knowing it shouldn't be there], it is okay, it is better than the first one [long silver swipe] I felt, but I would probably go to far with it too. But I feel like... It is at least more comfortable than the longer one. So the shorter size is better.
Fine as is	022 [8304-8531]	Assuming we are doing a swipe, I would suggest doing a rectangular shaped device [pointed to long silver swipe] would be definitely better, because it generates the idea you have to do a swipe. A starting point is much helpful.
	009 [4852-5076]	I really don't know. If I were to change something. Probably not too much. Because again working with the index fingers its just about right for the size of the fingers, so I probably wouldn't change that (video 7:28-7:35).
too short (no support)	001 [5345-5457]	Well there isn't enough space right if you are supposed to put it here [using round purple device] (video 3:17)
	032 [3269-3387]	And there is no support back here, and I don't know why. It's just not as comfortable as this one [long silver swipe].
	020 [9202-9425]	(video 14-14:15) And then for this one [round swipe] I would probably add a little bit more so your finger as you are pulling across maintains the flatness [increase size --would add material to the end of the form factor]
	002 [7526-7608]	But here your finger is not getting any support in this area. But here so I guess.
	020 [5921-6161]	However there is no, I like the sensor --- there is a resting. Kind of so you can hold your finger a little bit steady as you go back [meaning the round swipe is too short and no material to support the hand/finger]. But I like that design.
	032 [4278-4440]	I think it is too short. Again I don't have a ... I know you only swipe for a second, but it doesn't feel.. it is not comfortable. I don't like that one as much."

	005 [4395-4573]	But this one [round swipe], some people have longer fingers than others and for me where I feel comfortable to start I am actually up on the bump. Because it is too short for me.
Width		
Variable	008 [5203-5386]	Actually as far as the width, if it could be one of those things on a printer where they change the width for the paper, then you could set it to the right width for your own fingers.
Fine as is	032 [4812-5009]	The beauty of this one is that it is kind of aerodynamic. This finger [using the index finger], the middle finger which is next to it, can kind of slide along and keep you on track [when swiping].
too narrow	008 [703-841]	sometimes, it is just awkward because they are so narrow. That it feels like you have to be really precise with where you put your finger.
	008 [2476-2654]	I think really it just needs to be about 1/2 inch wider. Men's fingers are bigger. So if I am having trouble, I don't know they would have. I'm not sure what else I would change.
	001 [3866-3896]	could have been a little wider
	001 [1983-2078]	Maybe this could be a bit wider. [pointed to the width of the groove where the sensor fits in.]
	023 [8046-8354]	I would just try to make it more like a.. I don't want to say wider than this, but ... more like something I wouldn't want to pickup. Or like something that would be guided on either side of my fingers. For design purposes you couldn't make it too tight, but I would design this so it is more guided as well.
	008 [1895-2131]	Again it's the narrowness issue that bothers me. Just because these ridges here that you have to get between and especially on the thumbs because they are so wide you are getting different parts of the thumb each time. (video 2:59-3:08)
too wide (like more compact)	032 [3478-3697]	(video 7:22-8) This one [square swipe] is a little too wide. I might tend to slide to one side or another. Again trying to just put my fingers on there I have to spread my fingers apart too far. So this one is too wide.

	009 [5445-5621]	I like the mouse shaped one (round swipe), I like the computer mouse shaped one just for the size its much more compact. It doesn't have the size [points to long silver swipe].
	033 [168-196]	It looks easy to use, small.
	009 [5747-6106]	(video 8:53-9:22) I guess I'm thinking in the practical situation if I am using this [long silver swipe] in a laptop or in a briefcase, to me that just seems large and bulky although fairly slender. This (round swipe) although it seems to have more thickness to it, being a little bit more compact to me makes it more conducive to smaller types of equipment."
	009 [4130-4227]	(video 6:25-6:53) It is rather large to me if you are going to be using it in certain situations.
Height		
too low	010 [3266-3437]	Shape? I think now the height is comfortable for me [in reference to round and square swipe]. This, I think this [long silver swipe] feels more smoothly. (video 6:22-6:33)
	010 [1722-1921]	(video 3:07-3:25) I think the height is not good enough. Because sometimes I just want to.. If you just want to make it .. Steady here .. And then you swipe this.. But the height is not good enough.
	010 [3266-3359]	Shape? I think now the height is comfortable for me [in reference to round and square swipe].
	010 [2430-2611]	Maybe just the height. I need to hold it in my hand to swipe something. You cannot swipe like this. (video 4:40-4:53). {Admin: Oh, because the rest of your hand gets in the way?} Yea.
too high	010 [1722-1993]	(video 3:07-3:25) I think the height is not good enough. Because sometimes I just want to.. If you just want to make it .. Steady here .. And then you swipe this.. But the height is not good enough. {Admin: Okay, so you are talking about the height off the table?} Yea yea.
Manual Holding / Positioning	032 [3698-3888]	This one [round swipe] is okay, it just doesn't feel as naturally comfortable as this one did. It is too bulky, it sits too high, and there is not a natural flow over the sensor part for me.

	001 [3031-3122]	If it was non-mobile, it would be much more difficult and would be less comfortable to use.
	001 [3519-3595]	Besides being able to hold it, I don't know if I would want it any other way
	003 [2251-2700]	Well I like the idea that I can pick it up and hold it because sometimes it reads it better. And versus to have to push down and there were a couple times I had to stand up just to get it to… being able to hold it makes it much easier. (video 3:30-3:50) [in video when she interacts with the device her index is extended and other 4 fingers are in a fist --- is this a training issue... Does opening your hand give you better performance? comfort?]
	001 [2752-2917]	Well the fact that if I had to leave it on the table to use, it would have been a lot more difficult. So being able to pick it up and move it around was great for me
Back Surface	008 [2200-2367]	Also, holding them I mean these are very light and easy to pickup. But I pretty much had to hold it in my hand in order to swipe otherwise I wouldn't get a good image.
	006 [2760-2941]	At the same time the sensor is not too rigid with the surface so when I swipe it [the sensor] moves. Anyways I have to hold it with my other hand in order to swipe it correctly."
	020 [1490-1624]	However, it is a little tricky. I feel like if I just set my hand down there and slid it moves, so I would probably hold it and do it.
	005 [2617-2808]	{ADMIN: So if you are saying if it is going to be stable, to kind of stick it down?} (video 4:01-4:08) Yea, somehow where it could turn but yet once you put your hand on it would not slide.
	023 [2206-2361]	(video 4:15-5:08) I think one thing about it is that it moves when I'm swiping. It just kind of bothers me, because I feel that I'm not doing it correctly.
	014 [3475-3711]	(video 5:30-5:40) I guess dislikes, even though it has the rubber backing to it, it seems to move around a little bit. So if you are putting any sort of pressure to it you've got to kind of hold it with the other hand to kind of stable.

	005 [3873-3912]	it was light weight and it would move.
	013 [4148-4421]	The only thing that I noticed when I was down there and I don't know if its about the actual shape, and it maybe the weight or whatever. But on here its not going to slide on here but on here it could [in reference to the device sliding on a desk surface] (video 6:22-6:30)
	005 [2163-2614]	(video 3:34-3:56) When I was doing my normal finger, my index, it was fairly easy to swipe. When I did my thumb I had to reposition it and I had to hold it because I normally did a little more pressure so I had a tendency to move it. So it is the fact that it was stationary I could go like this but couldn't pull [dragging the sensor with his finger] like this, then it would be more easier because I have a tendency, I'm heavy handed to drag things.
	014 [3475-3711]	(video 5:30-5:40) I guess dislikes, even though it has the rubber backing to it, it seems to move around a little bit. So if you are putting any sort of pressure to it you've got to kind of hold it with the other hand to kind of stable.
	023 [4320-4447]	definitely would design it didn't move so it somehow stuck to with air or something sticky so it didn't move [while swiping].
	014 [4033-4132]	The only thing I'd put more of an abrasive backing on it or anchor it a little more to the surface.
Not Intuitive		
Shape	005 [4578-4823]	(video 7:08-7:26) This one it is just … it dents down in the middle [square swipe].. I don't really you know. Its like bending your finger the wrong way. I just. That one feels the most uncomfortable. That would be my last choice [square swipe].
	022 [5429-5762]	(video 9-9:28) I guess no. The shape threw me off a bit. Especially the curve on this side, this one. I mean it looks cool, but it kind of through me off in the sense the slide is down, so it is contrary to if you want to go down the slide, where as you want to come up in this case. So it is kind of counter-intuitive in that sense.

	033 [3789-3915]	This one [square swipe] doesn't give you much instruction. I realize it has this concave thing going on here. It is just okay.
	033 [5195-5456]	This one [square swipe], if I just looked at it and didn't know, it isn't quite as intuitive, I'm repeating myself here. It's square and indented. At first glance in our high tech world that could be any number of things, but not sure it's a fingerprint sensor.
Movement (swipe)	020 [6904-7288]	(video 11:09-11:40) I mean this one [square swipe] just has the look that you have to be holding it when you use it with the concaveness of the sides [pointing to exterior sides]. But again, I feel like I'm intelligent enough to figure it out, but had I just walked up to it and didn't know anything about it, I wouldn't or bought it even, I think it would be difficult to figure out.
	032 [330-701]	(video 0:25-0:49) It is cute, I don't know. Knowing that it is a fingerprint sensor, I would just think that I would put my hand on, my middle finger on the thing. Like that. I think of it as being like a mouse maybe. Even though I don't know what its purpose is. At this point in time, I would just place my finger like that [place finger on black part of silver swipe].
	012 [3146-3333]	Well I kind of did, because it [square swipe] was skinny, so like you had to scan it to get the image. But when I first saw it [square swipe] it looks flat like you just press it on there
	012 [2899-2965]	Well I wouldn't know if this [square swipe] is a swipe one or not.
	021 [11740-11817]	The only concern I have this one is that you feel like you should stay there.
Alignment / Start-Stop	021 [10798-11239]	(video 14:54-16:18) [round swipe] I love this color, so I am already persuaded that these should be the way to go [laughs]. Now this one [round swipe] took in some of the things I talked about, kind of guiding the finger a bit more, but without some kind of direction, I am almost feel like you want me to leave your finger there because that is a cozy little cradle for my finger. I'm not getting the idea here that you want me to move it.
	020 [799-930]	(video 1:15-1:32) But I would guess you would drag your finger across it somehow. But, I'm not sure how fast or when it would read.

	004 [3267-3363]	I think just the person has to be aware that they can't place their whole finger on it and swipe
	020 [166-205]	I wouldn't know how to place my finger.
	023 [166-443]	(video 0:27-0:40) I guess my first thought are I would wonder how something with a window that size would pickup your finger. I'm guessing you put your finger somehow like this. I guess that my first thought would be I wouldn't know how to use this unless someone told me how.
	008 [3428-3854]	I think it aided once I got the hang of it. Its not intuitive from looking at it what you are trying to do. I think just because there so much area before the part that you are swiping. The fact that you are starting up here it just seems like you are trying to get more of an image than what is actually recorded. But I'm not really sure how to change that. It might just be an issue of instruction manuals. (video 5:39-5:55)
	004 [4788-5166]	I just think I don't know I just feel that one is a lot easier to use… just place your finger rather than swiping it. I don't know, you probably know more than me but I feel there is more chances of you not swiping right. You know its everyone knows just to place their finger and that's all. Not everyone knows here like to put just this part of your finger here and swipe down.
	023 [3755-3924]	Probably like this. I think in the beginning I would just think I really wouldn't know what to do with it. It's not very easy to tell how to interact with it right on.
	020 [5339-5639]	(video 8:40-9:05) [discusses square swipe] This one complete chaos. I don't know what they want me to scan, what part of my finger, even where to begin. Or even had I not known from seeing this one [silver swipe sensor] the sensor going this way, I could have assumed that way. Just very oddly shaped
	023 [851-1208]	(video 1:16-1:52) I would think assuming I would probably put it too my left. So assuming I would have to put my finger over it, not knowing how to use, there is a blue section up here so I'm assuming you have to start up here and put your finger over it like that or scan it over. The other option would be to hold a portion of your finger over the window.

	033 [4458-4750]	For this one [square swipe], it is just not visible to me that it is a fingerprint sensor and if I didn't know anything about them, I probably wouldn't know where to start and stop and what was expected in even the direction of the swipe. You could do different things with that potentially.
Other	030 [3160-3346]	I like the color and the style of it. Its nice and comfortable enough for me. I don't know about other individuals who have bigger hands and longer fingers, how they would feel about it.
	023 [2749-3054]	(video 5:15-5:40) Maybe if there was some sort of light or something to show you that you correctly, maybe not that you passed, but that you correctly swiped it - like a green light or something right here [on the hump of the sensor] to make sure I was doing it correctly would help. Some kind of feedback
	003 [2976-3151]	Just push harder if you can't pick it up and on one of them over there I actually had to use my other hand to help. The harder I pushed, the better it read. (video 4:22-4:25)"
	030 [3430-3686]	(video 7:21-7:48) No, I think it is pretty much fine and functional as is. It pretty much fits my hand. I've noticed that I have a shorter at the end of the finger, and that might just be me because I'm short, small it feels like I'm not doing it correctly
	013 [5259-5751]	(video 7:57-8:57) Yea, I guess the only thing I would do I know the sensor is here is put the sensor further down here [move sensor more towards the cable]. Does that make sense? Because a person automatically puts there hand here and now draws across as opposed to if you put it down there despite putting it there would the sensor still pick it up or would you have to draw it across for it to pick up? If I just put my finger there would the sensor pick it up? Or do I have to go across?"

Appendix S. Push and Pull Design and Fabrication Images

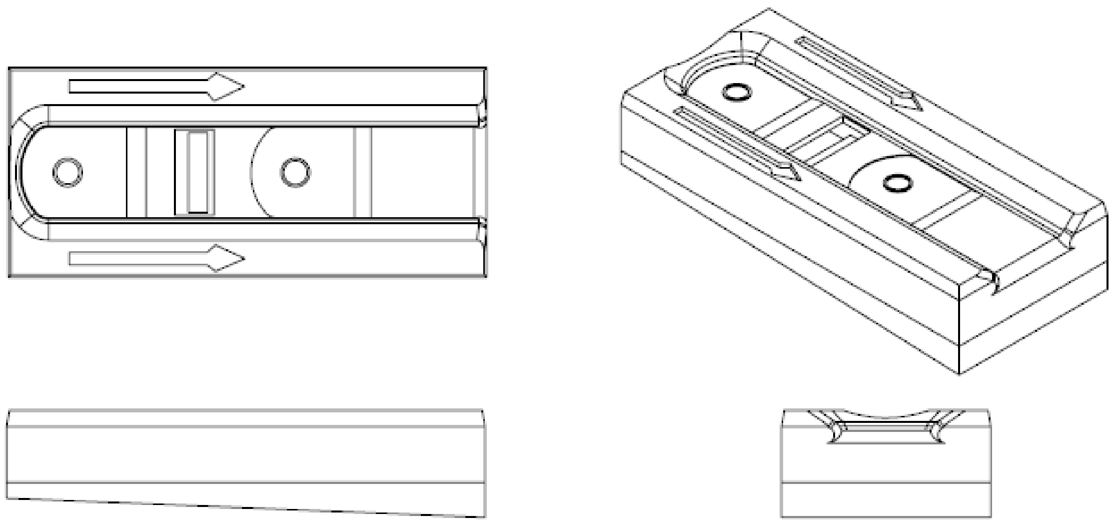


Figure 119 Top, front, right side, and isometric views of the pull form factor.

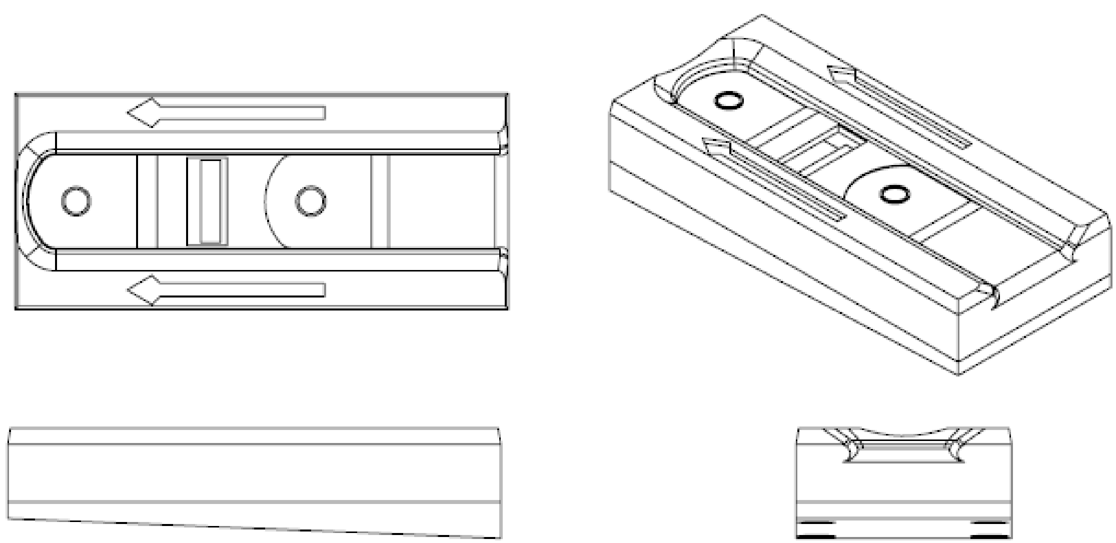


Figure 120 Top, front, right side, and isometric views of the push form factor.

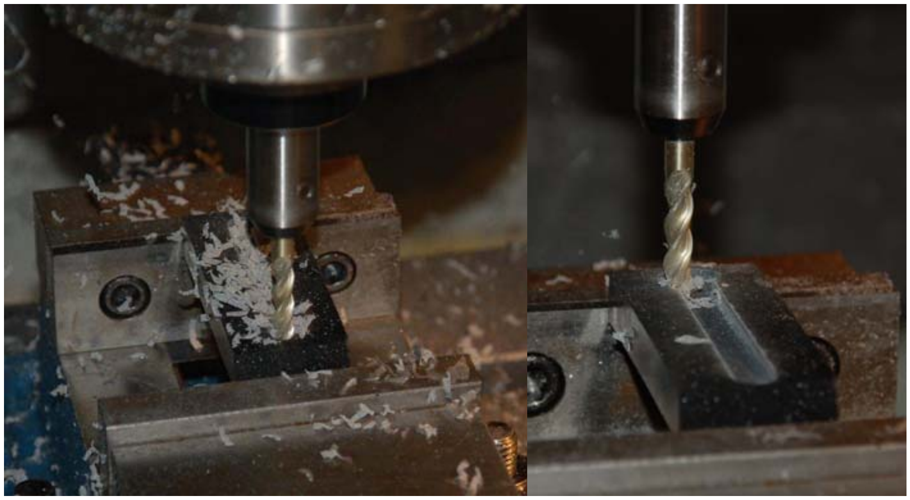


Figure 121 Step 1 of the manufacturing process that created the finger channel.

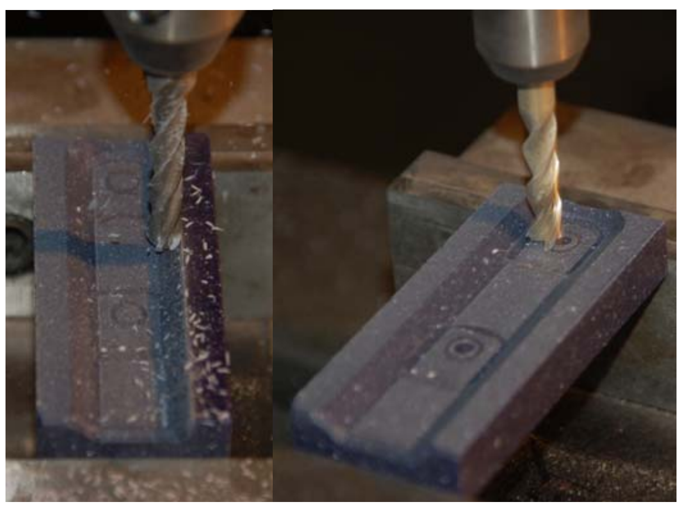


Figure 122 Step 2 of the manufacturing process that finished the channel and created the tactile and visual start and stop cues.

Figure 123 Step 3 of the manufacturing process that created the arrows indicating direction of the swipe.

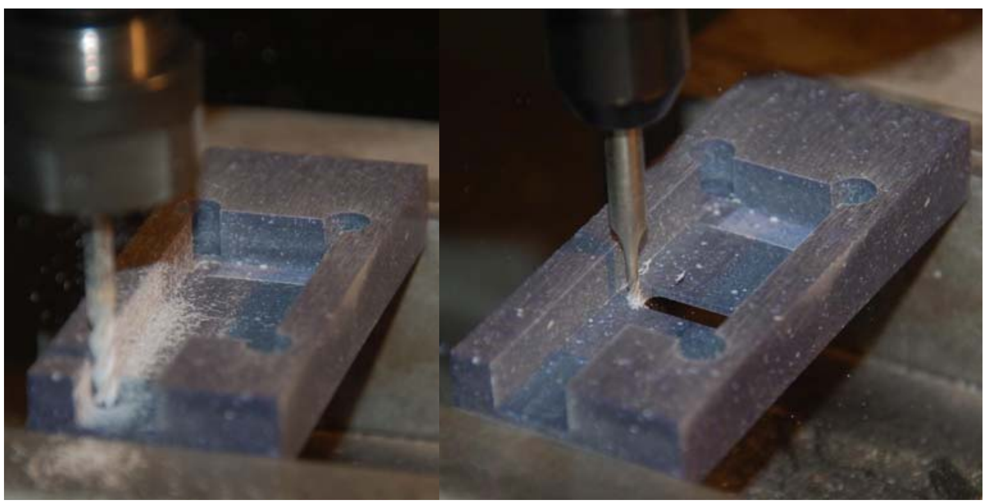


Figure 124 Step 4 of the manufacturing process that created the area where the fingerprint sensor circuit board was housed.

Appendix T. Model adequacy checking for Aware and NFIQ image quality scores

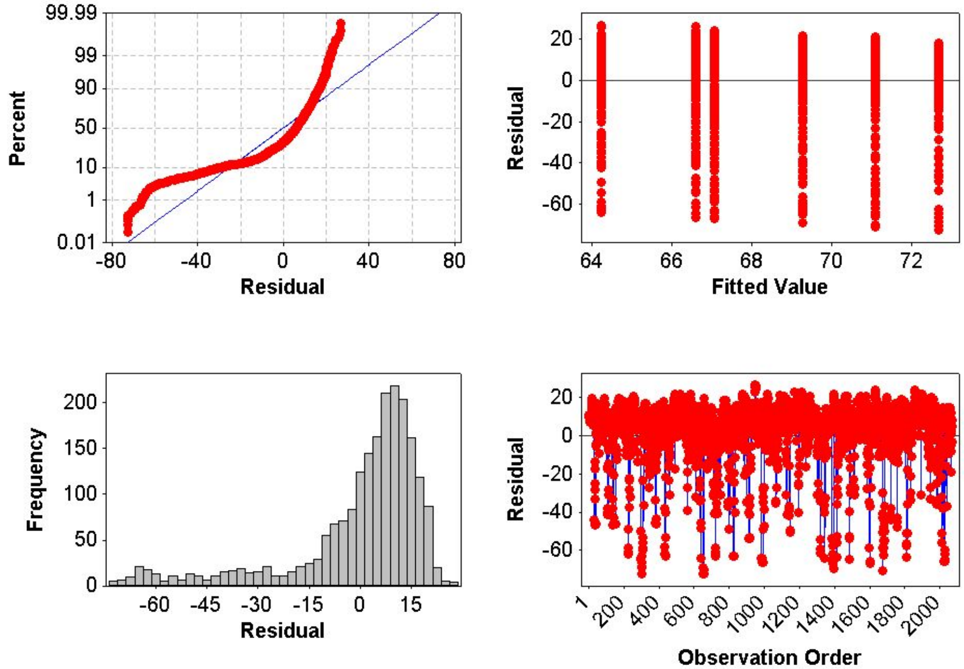


Figure 125 Diagnostic and residual analysis for Aware IMQ for training.

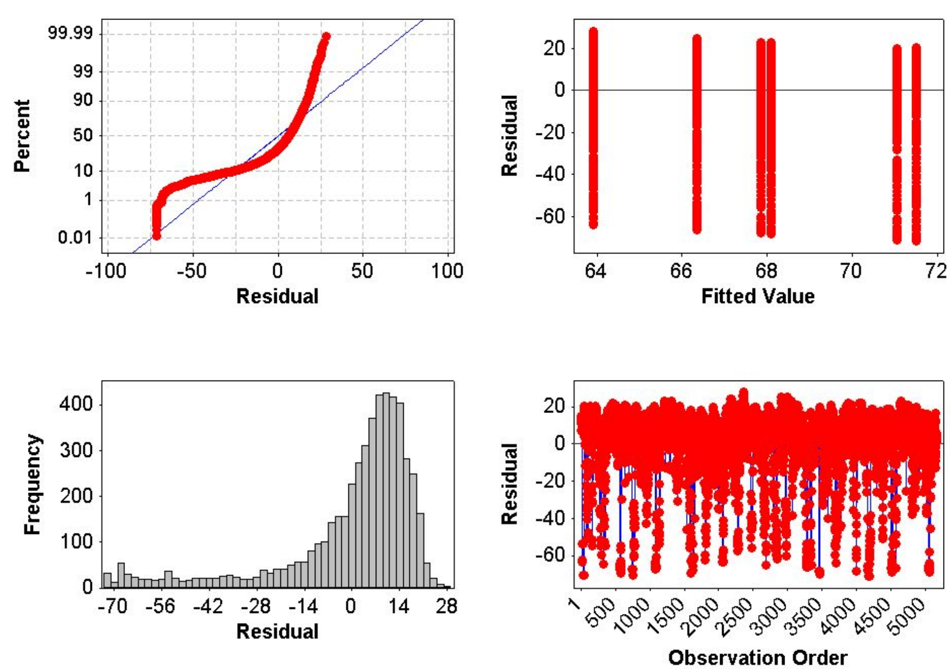


Figure 126 Diagnostic and residual analysis for Aware IMQ for enrollment.

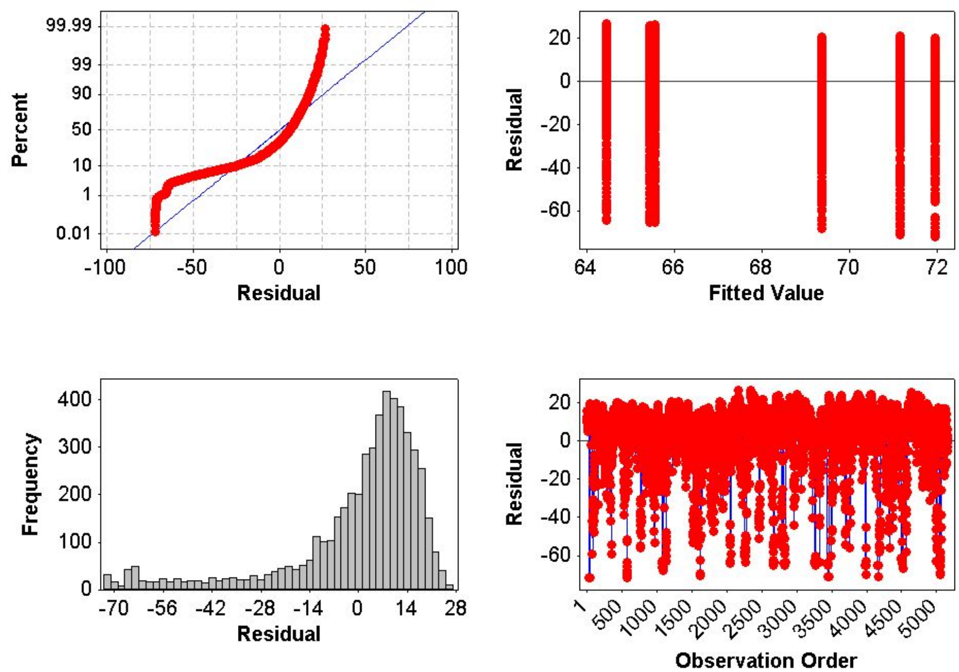


Figure 127 Diagnostic and residual analysis for Aware IMQ for matching visit 1.

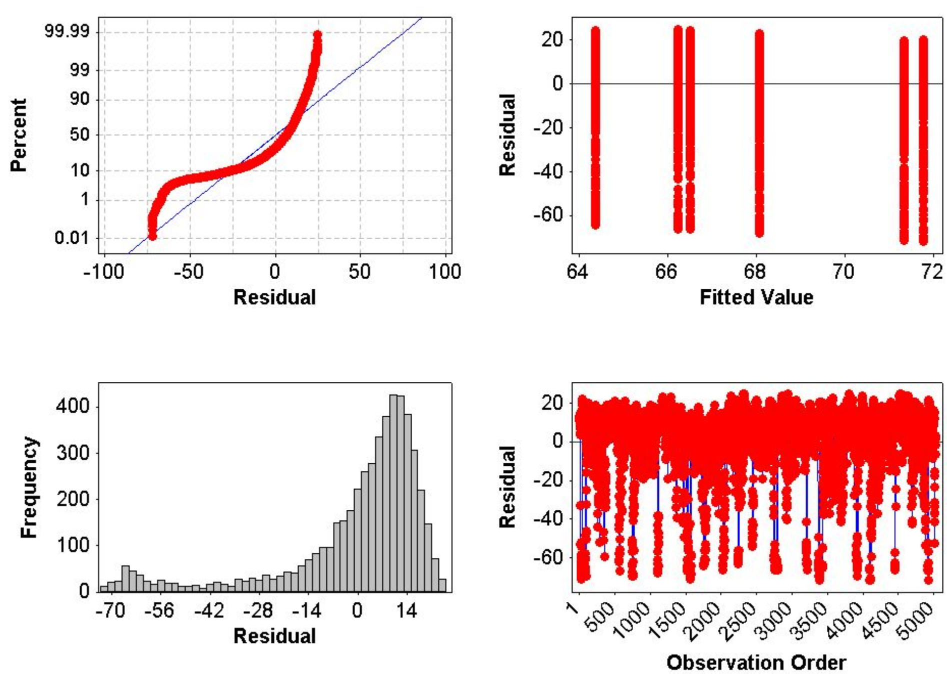


Figure 128 Diagnostic and residual analysis for Aware IMQ for matching visit 2.

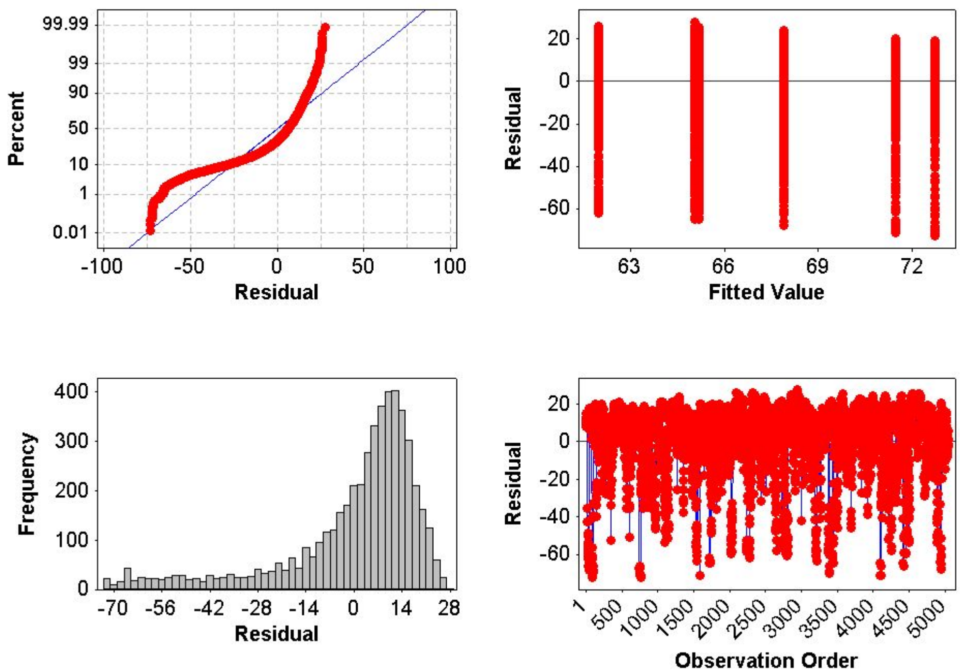


Figure 129 Diagnostic and residual analysis for Aware IMQ for matching visit 3.

Appendix U. Model adequacy checking for the number of detected minutiae

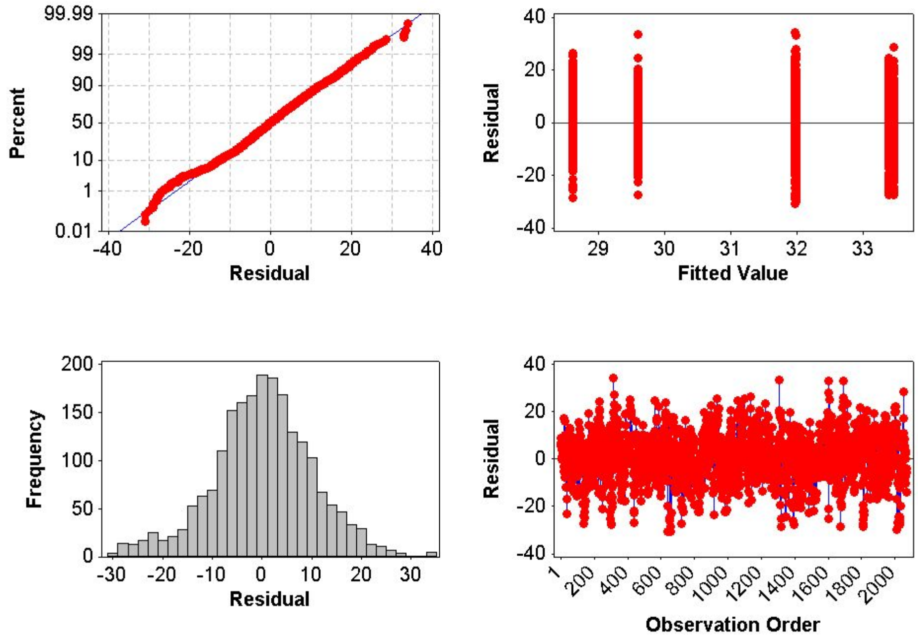


Figure 130 Diagnostic and residual analysis for the number of detected minutiae during training.

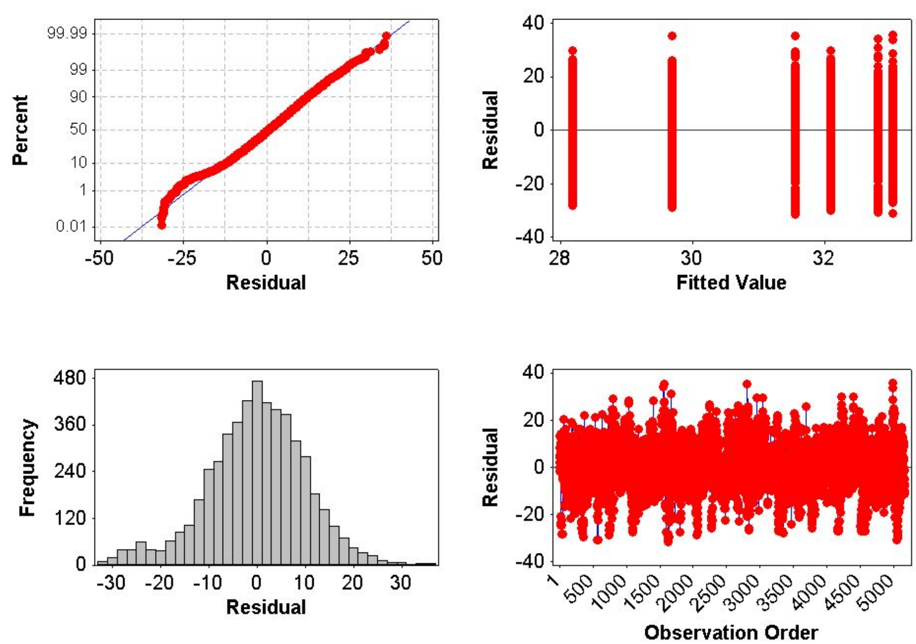


Figure 131 Diagnostic and residual analysis for the number of detected minutiae during enrollment.

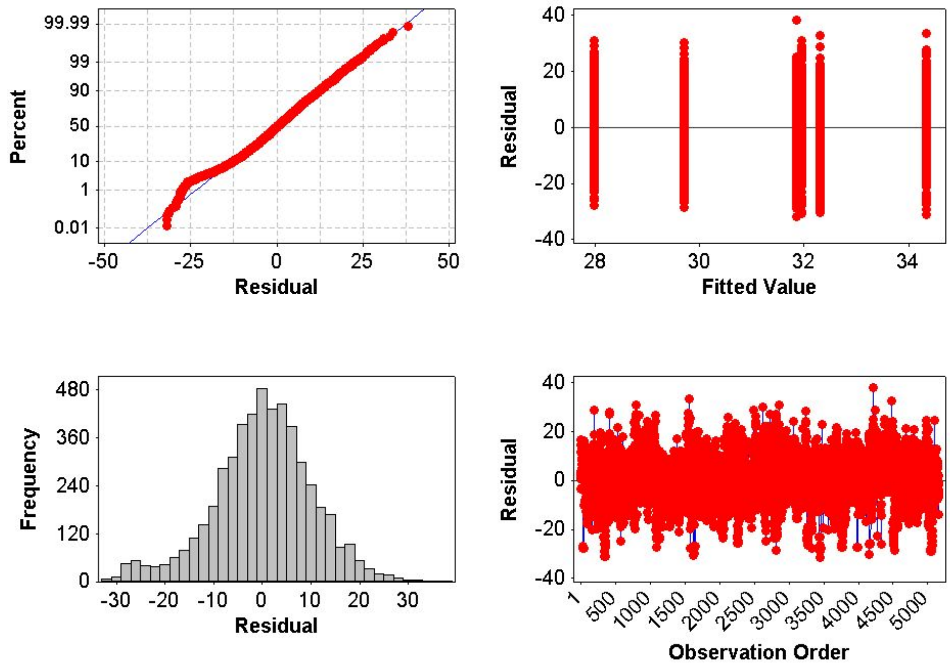


Figure 132 Diagnostic and residual analysis for the number of detected minutiae during matching visit 1.

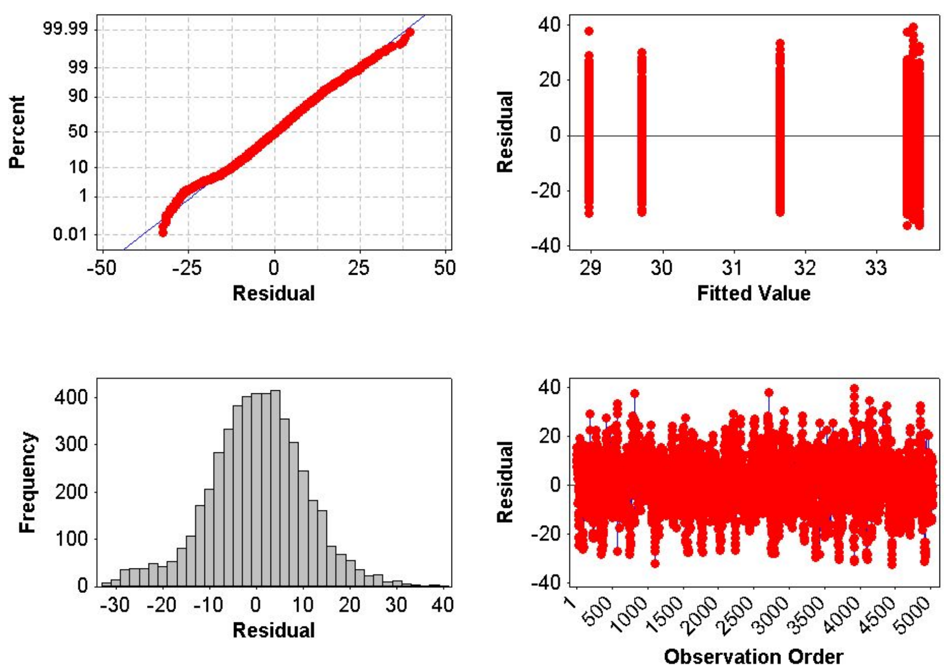


Figure 133 Diagnostic and residual analysis for the number of detected minutiae during matching visit 2.

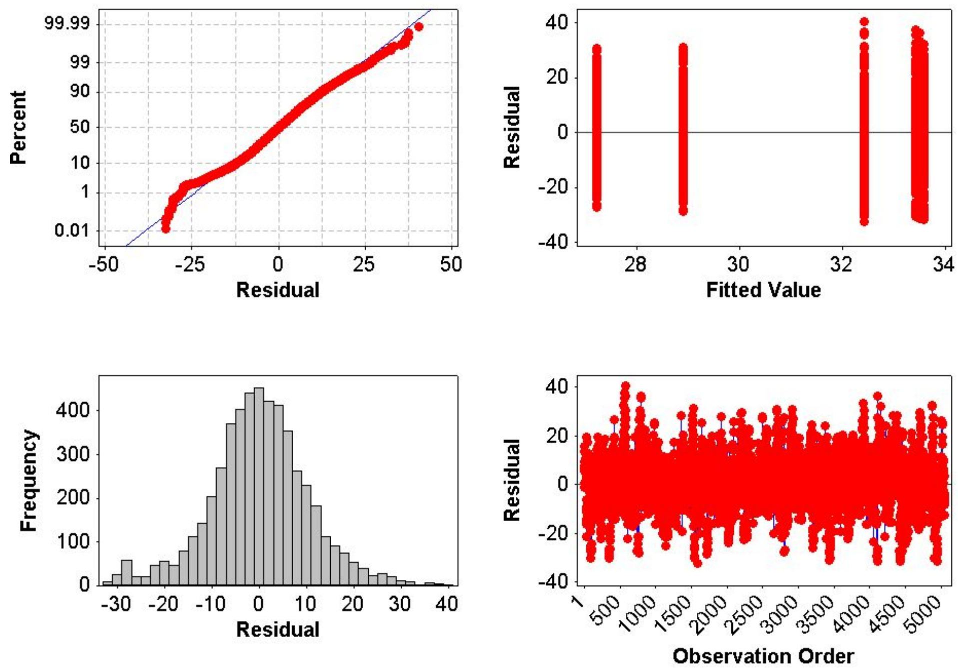


Figure 134 Diagnostic and residual analysis for the number of detected minutiae during matching visit 3.

Appendix V. Model adequacy checking for fingerprint image area

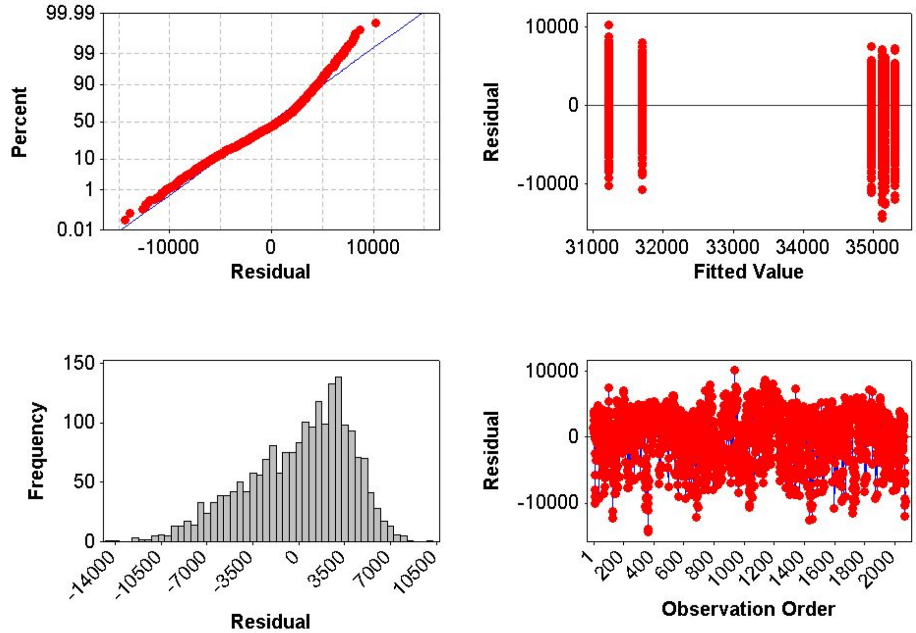


Figure 135 Diagnostic and residual analysis for fingerprint image area and training.

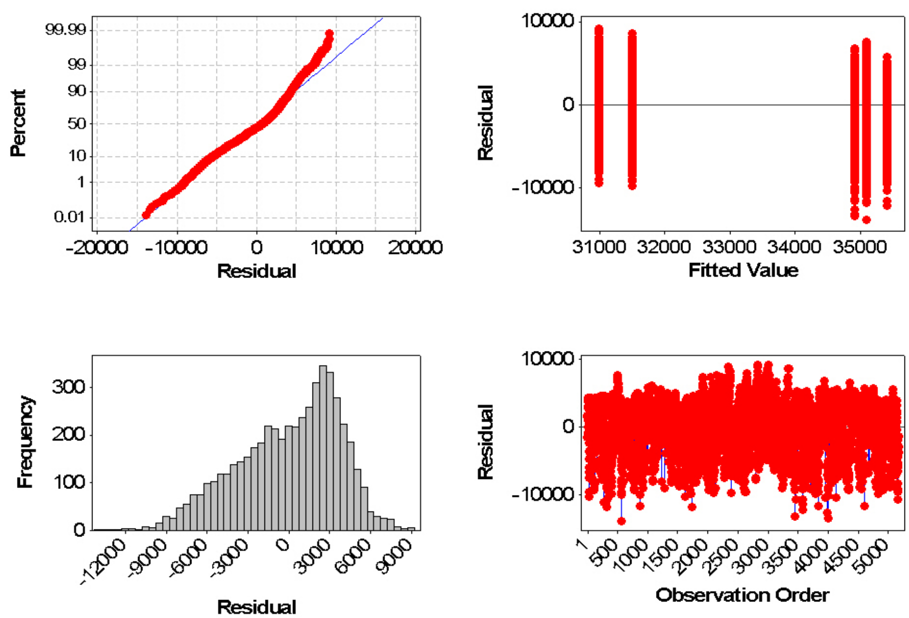


Figure 136 Diagnostic and residual analysis for fingerprint image area and enrollment.

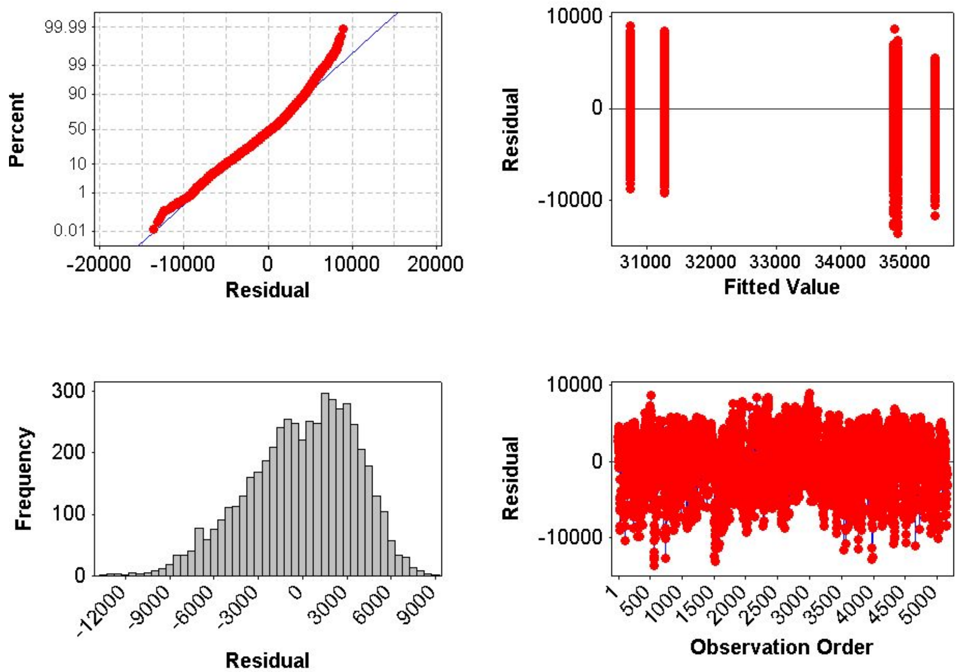


Figure 137 Diagnostic and residual analysis for fingerprint image area and matching visit 1.

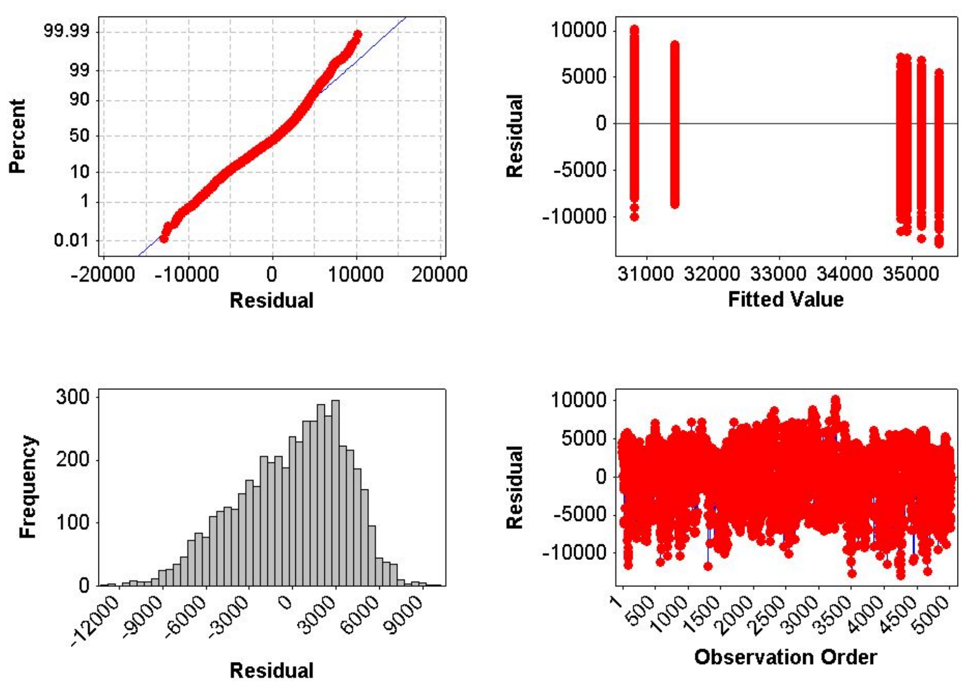


Figure 138 Diagnostic and residual analysis for fingerprint image area and matching visit 2.

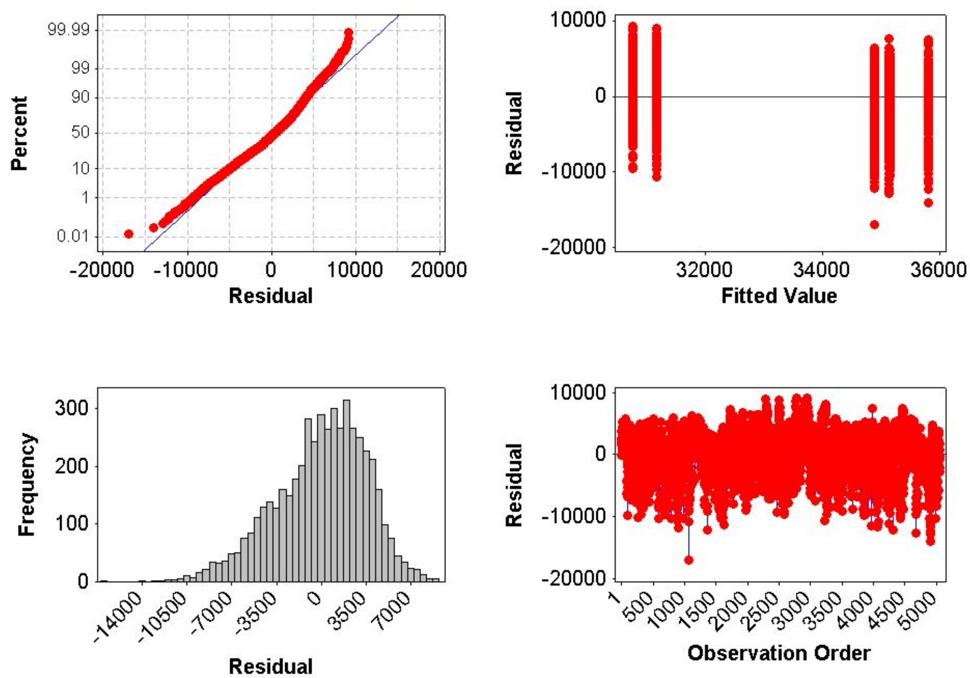


Figure 139 Diagnostic and residual analysis for fingerprint image area and matching visit 3.

Appendix W. Model adequacy checking for the fingerprint image contrast

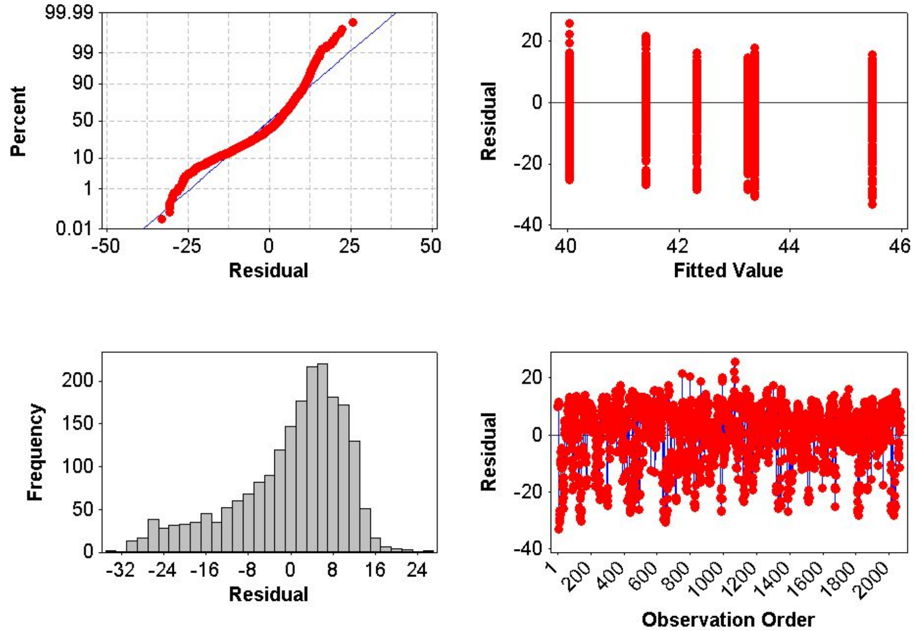


Figure 140 Diagnostic and residual analysis for fingerprint image contrast and training.

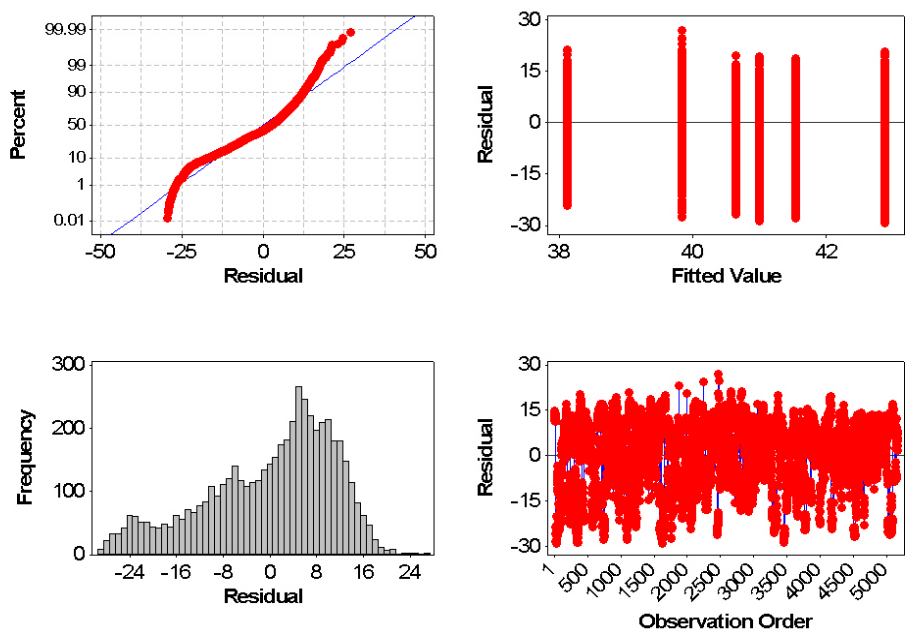


Figure 141 Diagnostic and residual analysis for fingerprint image contrast and enrollment.

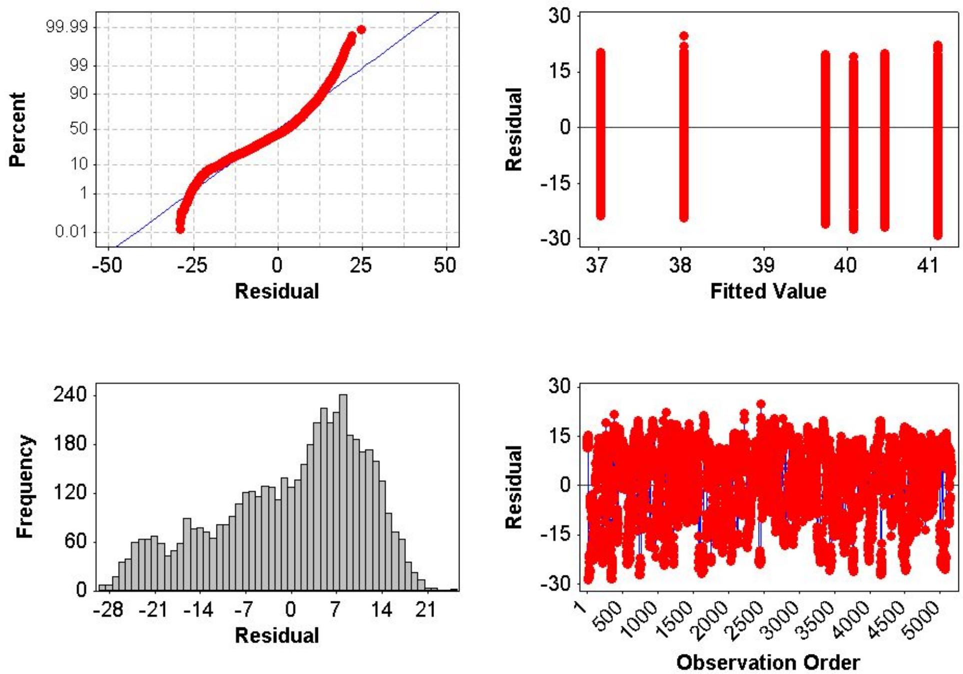


Figure 142 Diagnostic and residual analysis for fingerprint image contrast and matching visit 1.

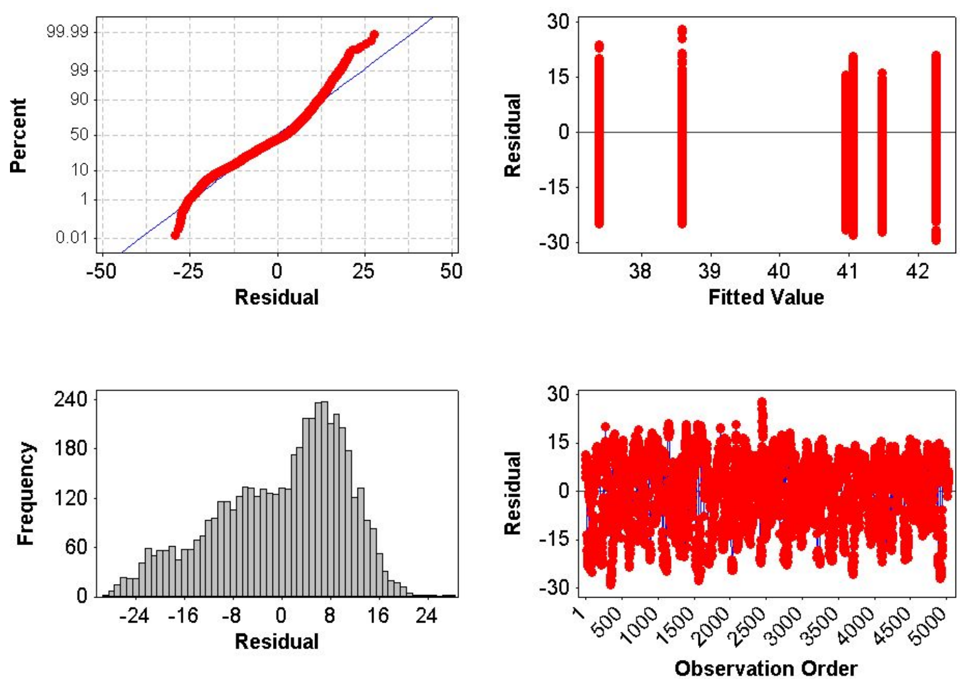


Figure 143 Diagnostic and residual analysis for fingerprint image contrast and matching visit 2.

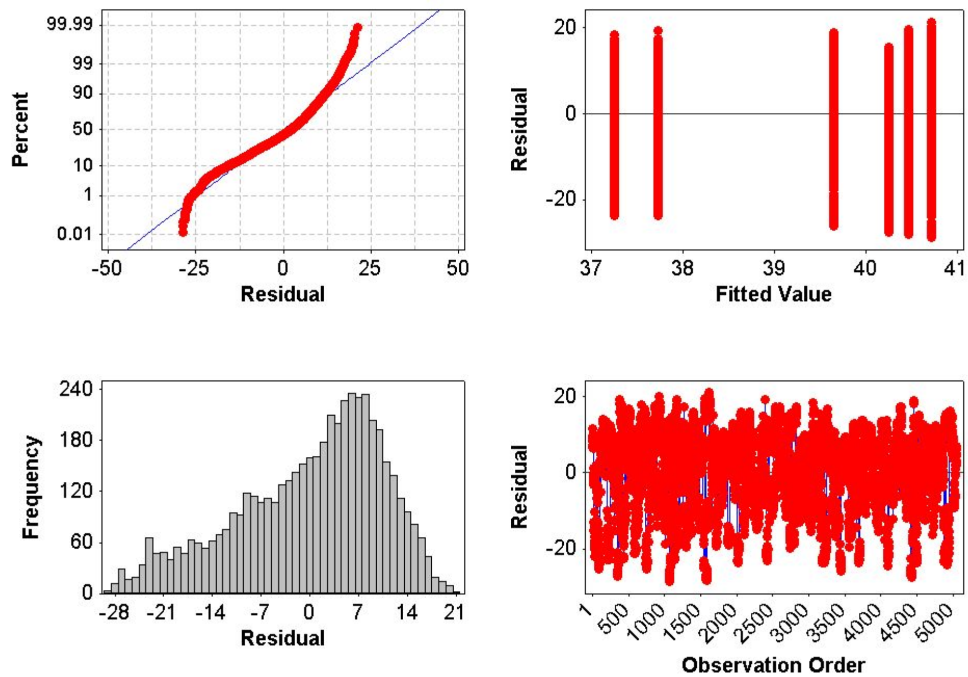


Figure 144 Diagnostic and residual analysis for fingerprint image contrast and matching visit 3.

Appendix X. Model adequacy checking for the user satisfaction survey

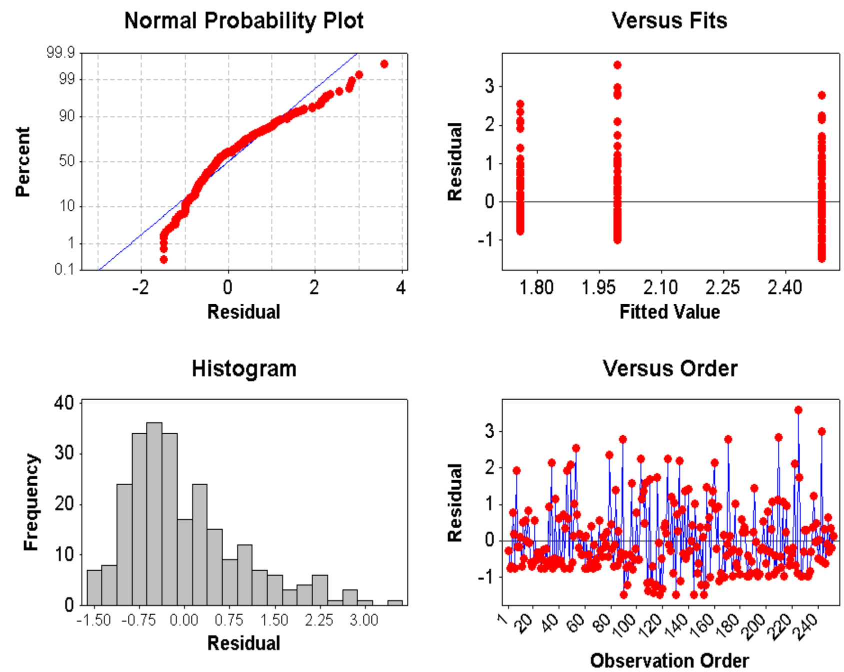


Figure 145 Diagnostic and residual analysis for the overall scale.

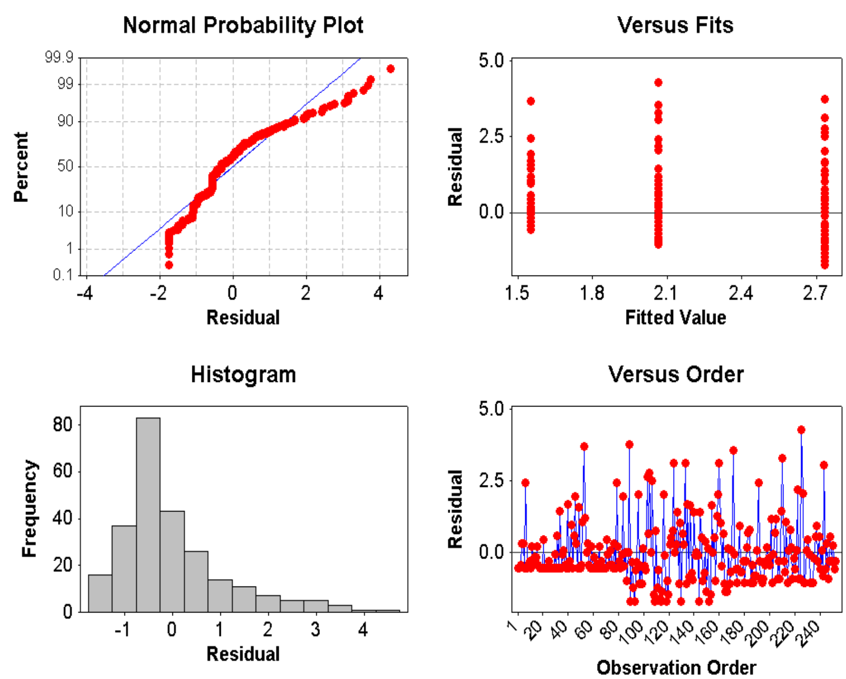


Figure 146 Diagnostic and residual analysis for system usefulness.

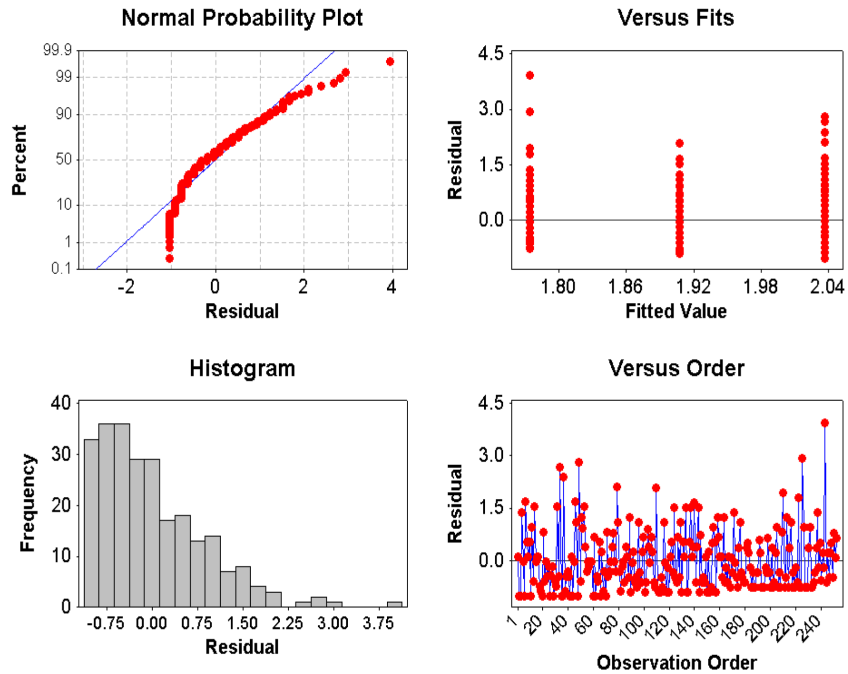


Figure 147 Diagnostic and residual analysis for information quality.

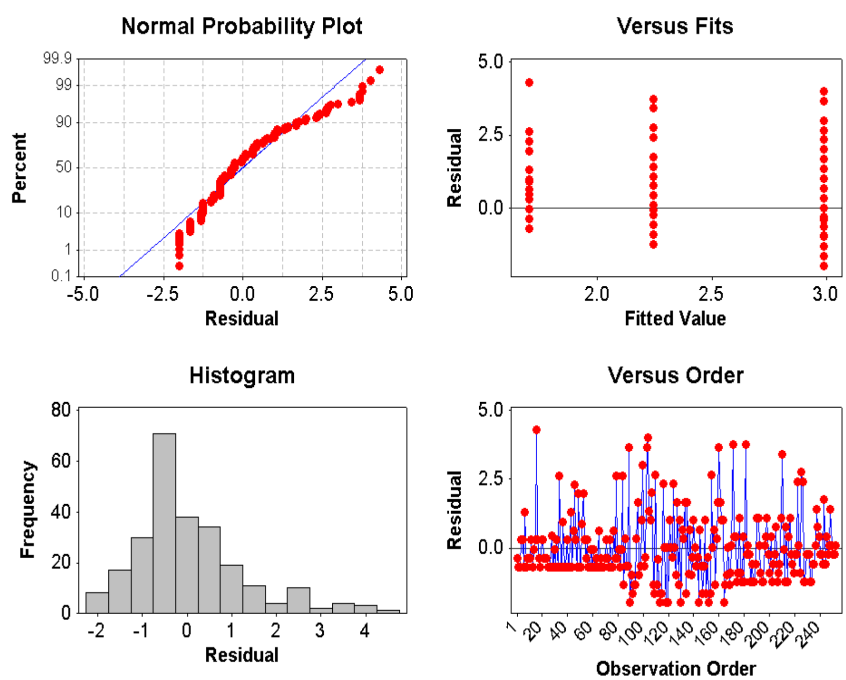


Figure 148 Diagnostic and residual analysis for interface quality.

Appendix Y. HBSI User Satisfaction Comments

The following participant comments were received during the post-study questionnaire. The comments appear as typed into the web application at the time of the survey.

ID	Open ended feedback or comments regarding any of the sensors used during this study.
1	The push sensor design was intuitive, but the images that came up on the screen did not seem to capture the entire fingerprint.
2	UPEK was much easier to use and seemed to be more consistent. I had problems with the PUSH in the beginning and still had to think about it constantly to get it right. The PULL is easier than the PUSH but I had the same problems.
3	I liked the large sensor better than all three of these push/pull sensors. :-)
4	I had a little trouble with PRESSURE since I have arthritis in my indexes. However, for the QUANTITY of swipes expected to be used in real life? This was a minor inconvenience. Thank you.
11	I liked the ramp effect of the UPEK. I think if the PULL sensor was angled I would like it much better because the channel combined with the angle would be more effective and comfortable. The PUSH sensor seemed to work pretty well. I don't think an angle on it would be effective, but, again, the channel was very helpful.
12	I found it more difficult to use the push due to the motion required. Not much difference between the UPEK and Pull other than the corridor of the pull was narrower.
14	UPEK is better than Pull sensor. I don't feel good on the push sensor.
17	I am not sure about this but I have a feeling that in my last study my fingers were more wet so it was easier to use the sensors.
19	upeck was best pull was easier to use than push just did not like push and it didn't pick up fingerprint easily either
20	UPEK, and PULL are good PUSH is a little bit hard for me to use, esp. with my left hand
21	For the UPEK, it is a little confusing, I can not remember whether to swipe the finger or put the finger on the sensor for a while. The PUSH sensor, it is a little uncomfortable. PULL sensor is best!

22	I felt like the UPEK had a clearer image, I did not have as many problems scanning with it, than with the others (Push and Pull).
23	Upek : It had an attractive design and also was very comfortable to use. I guess the only issue was if it had a visual sign to tell us which direction to swipe (like in the PUSH & PULL). Once I knew the direction, it was very easy to use. PUSH: was bulky and it felt very odd to push my finger away from me. PULL: was bulky but at least more comfortable since I was pulling my finger towards me.
25	I like the overall design of the UPEK Sensor because it was design with the curve of the finger. Both the push and pull sensors were flat and didn't work well with the overall curve of the finger.
26	I liked how the UPEK sensor was curved. It made it easier to swipe your finger. The PULL sensor was my least favorite because it was not curved so it was harder to pull my finger across it. The PULL sensor was a little uncomfortable. I liked the PUSH sensor because it was easy to understand, and it was comfortable to use.
27	UPEK sensor provide most user friendly when compare with PULL and PUSH. However, PULL sensor is a second preference as far as ease of use and effectiveness. The PUSH is the least prefer due to the pushing motion.
31	I prefered the Push and Pull sensors over the Upek.
33	The visual cues of the upek were not very clear though i found it to be the most pleasant to use.
34	Upek is smooth and very comfortable. Both the Push and Pull feel more uncomfortable, more impersonal.
35	The push and pull sensors were the easiest to use and the upek was a little more difficult
39	Sometimes I have to think a while to distinguish between the push and pull sensor. For some reason, I think the colored dots made it confusing. Maybe having just the arrows would be enough.
40	Pushing was awkward to do. The arrows are really helpful. The UPEK had a natural feel when you pull upwards and back.
43	Large Area was best. UPEK also ergonomically-designed well. Pull was satisfactory. Disliked PUSH.
44	For both the PUSH and PULL sensors, they felt more awkward using with my non-dominant hand.
47	UPEK didn't always register the swipes as well as the PUSH or PULL, PUSH always felt comfortable to use even though I thought the PULL would be the easiest to use

48	I felt the PUSH and PULL sensors were hard to accurately swipe my finger across at times. I think it was due to the flat design on the top and if it were more curved like the UPEK it might be more natural feeling to use.
49	The Upek seemed to me the most easiest and reliable to use.
50	I am not sure these sensors have any significant application in everyday life. I found them to be cumbersome and that could be due to the routine that I had to do in order for the study to be done. If I had to use them everyday I might have a different experience.
54	The arrows on the PUSH and PULL are helpful if someone weren't shown a demonstration on how to use them before trying it. The UPEK doesn't have that feature and it could be confusing if a user didn't know to start with their finger on the blue dots.
55	I preferred the push as it was the one I could get to work most of the time. Actually the large was the easiest. The upek was comfortable but hard to get to work and I don't think I ever was able to use the pull.
57	If it was my job to take finger prints, my choice instrument would be the upek. It is an attractive tool and the patient would be more comfortable with it.
58	Using ensors that required a pulling motion is much more natural.
61	The curved surface on the UPEK made it easier to swipe because it's more typical of a finger bending. I felt like I had to use a lot of force on the PUSH, possibly just because it was a different direction than the others.
62	I believe the angle of the sensor on the table makes a big difference in the accuracy of the print. For example, if the sensor was completely 90 degrees verticle [vertical], it would be difficult for me to position my hands on the sensor, as opposed to a slightly rotated sensor, depending on which hand was tested. Overall it was great! Thanks
63	UPEK was definitely the most comfortable and easy to use. With the PUSH and PULL, I would mess up more often and the fingerprint wouldn't capture.
64	I liked using the UPEK sensor the most. I never had a problem with it capturing any of my swipes, the same with the PULL sensor. The PUSH sensor sometimes did not capture my fingerprint the first time and seemed to be very sensitive to how the finger was swiped across the sensor.
66	I liked the pull sensors better as I understood better that the scan was complete upon passing the scanner. With the push sensor I was not sure when the scan was complete. (it would be hard to tell if the finger print image did not appear on the screen.)
70	I think the UPEK was the best sensor to work with out of them all.

72	I liked the pull censor best. It was the easiest to use and understand how to use. The pull censor took a little longer to obtain the print but it was still an easy censor to use. Upek was also a good censor, but it had less visual clues or cues on it to understand how to use it.
73	UPEK and PULL were very similar, though i prefered the slight curvature and smooth feel of the UPEK. The PUSH sensor felt odd when pushing my finger over the sensor.
74	little cumbersome to use the push sensor. However overall easy to do.
75	The PUSH sensor, if any, was the most awkward to use since it was the only one that changed the motion of your hand.
76	I think that my response regarding the PUSH sensor is directly related to my prior experience with fingerprint sensors. It felt odd to move my finger in the opposite direction than all other sensors I have worked with. Also, I felt that the way the finger looks distorted on the captured images made an impression on me. The tip of the finger looked 'squished', in comparison to images captured with either the UPEK or the PULL sensor. I did prefer the tactile feedback on both the PUSH and PULL sensors over the simple channel of the UPEK sensor.
78	Upek was the easiest.
79	I liked the UPEC a lot. I hated the PUSH, it was hard and did not always capture my finger prints. The PULL was fine but not as nice to use as the UPEK.
80	I didn't like the push sensor.
81	I liked the UPEK more because it was smoother to move my finger across it. I thought that made it easier.
83	The Push/Pull sensors are nice because they help channel your finger over the scanner. The Push doesn't function like I would immediately expect a fingerprint scanner to, but I liked it best in the end.
84	All of the sensors were easy enough to learn how to use. I would have no problem using one of these sensors at a later date.
85	UPEK- was easy to use and my finger slid over it easily. The push and pull both "grabbed" my finger at times preventing a smooth swipe.
87	The only reason I did not like the UPEK as much is because it was harder to get it to register(could just be me) other than that they were all easy to follow and see the directions.

Appendix Z. Model adequacy checking for Efficiency

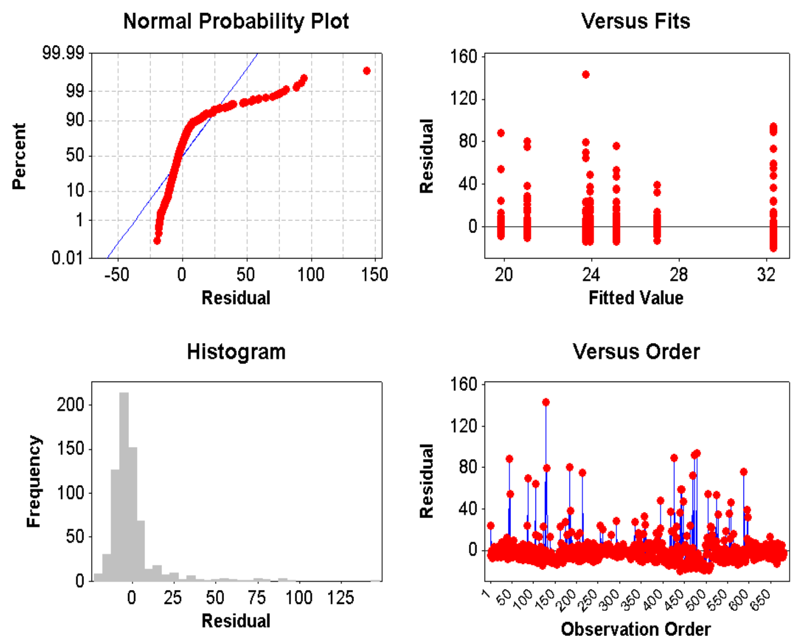


Figure 149 ANOVA model adequacy analysis for training task time.

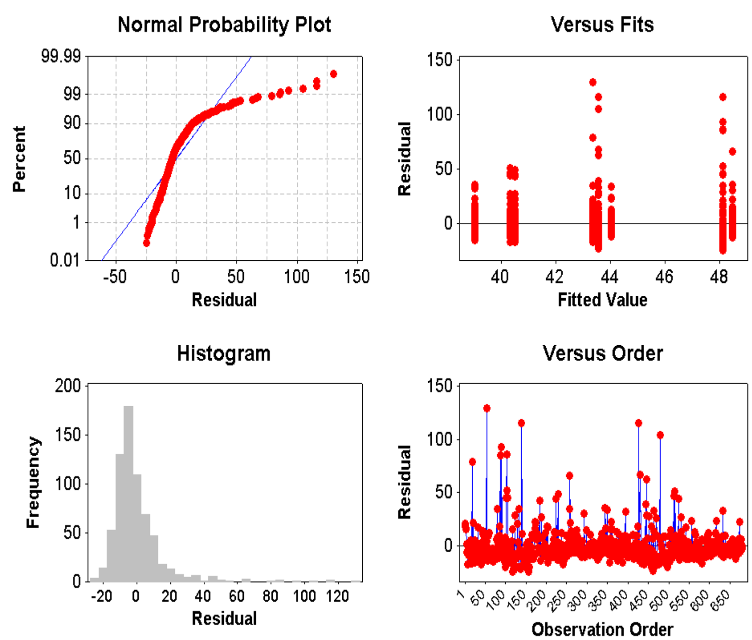


Figure 150 ANOVA model adequacy analysis for enrollment task time.

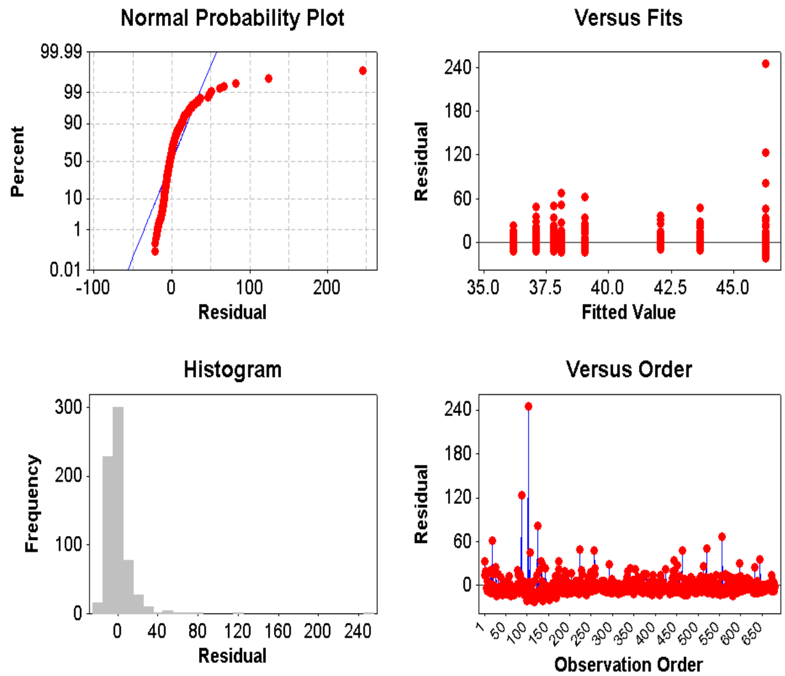


Figure 151 ANOVA model adequacy analysis for matching visit 1 task time.

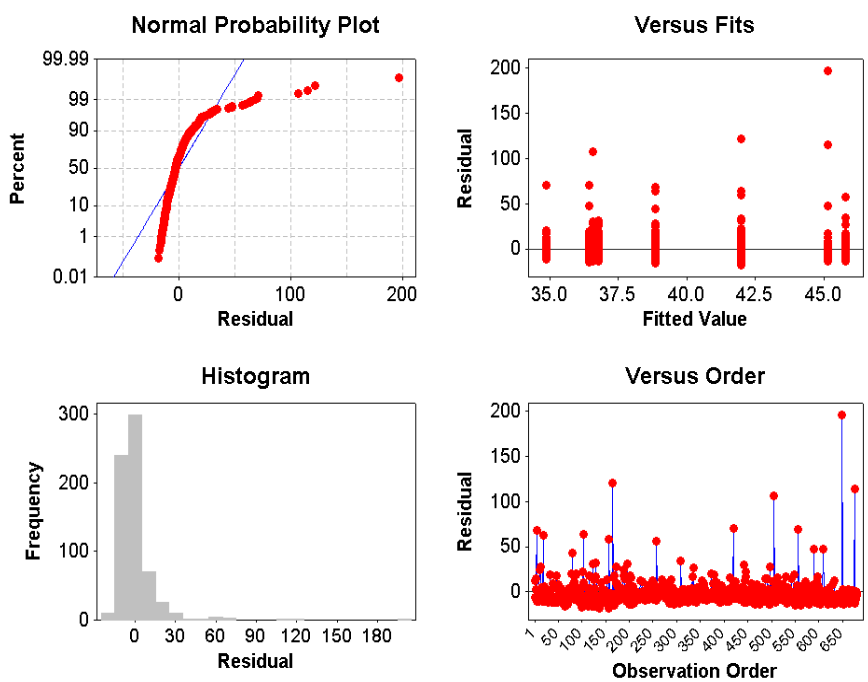


Figure 152 ANOVA model adequacy analysis for matching visit 2 task time.

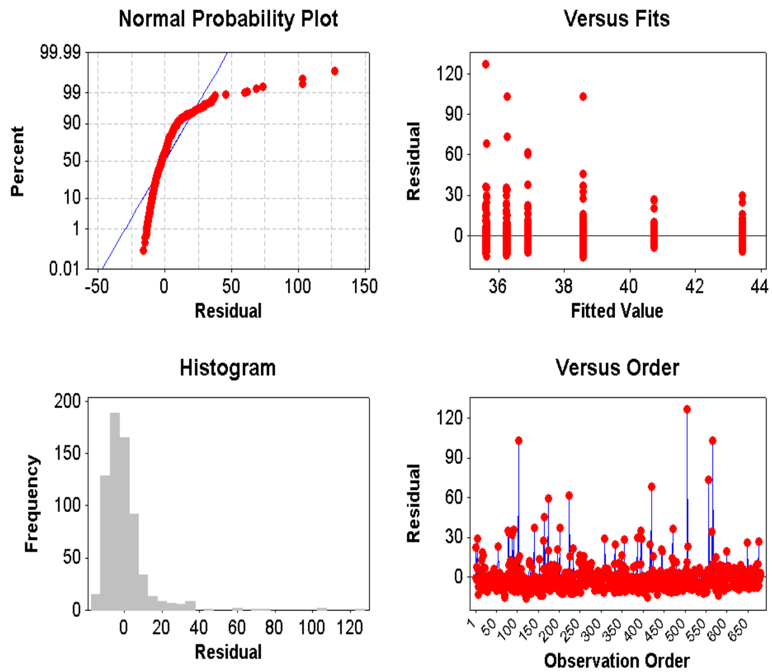


Figure 153 ANOVA model adequacy analysis for matching visit 3 task time.

Appendix AA. Box plots for Efficiency Measured by Task Time

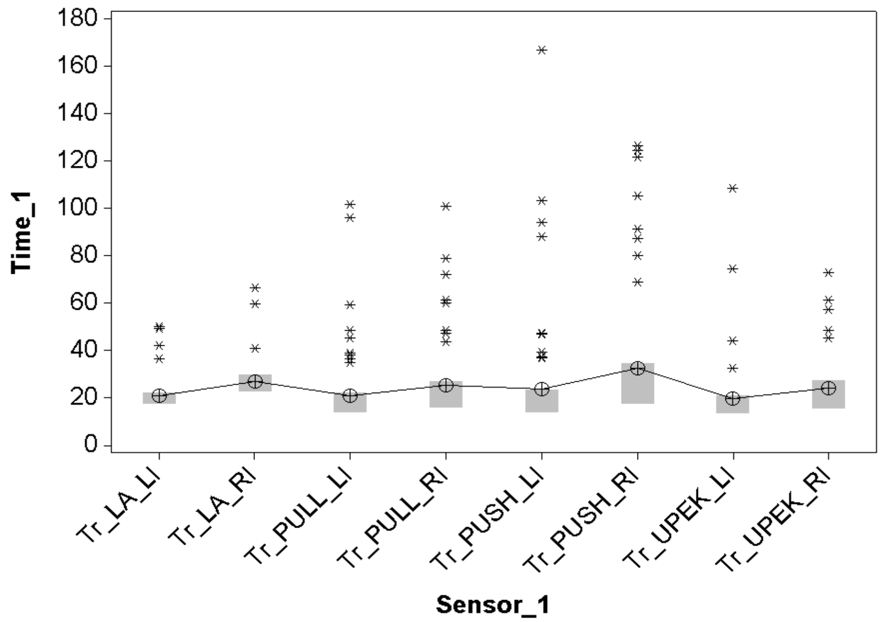


Figure 154 Box plot of training task time by sensor and finger.

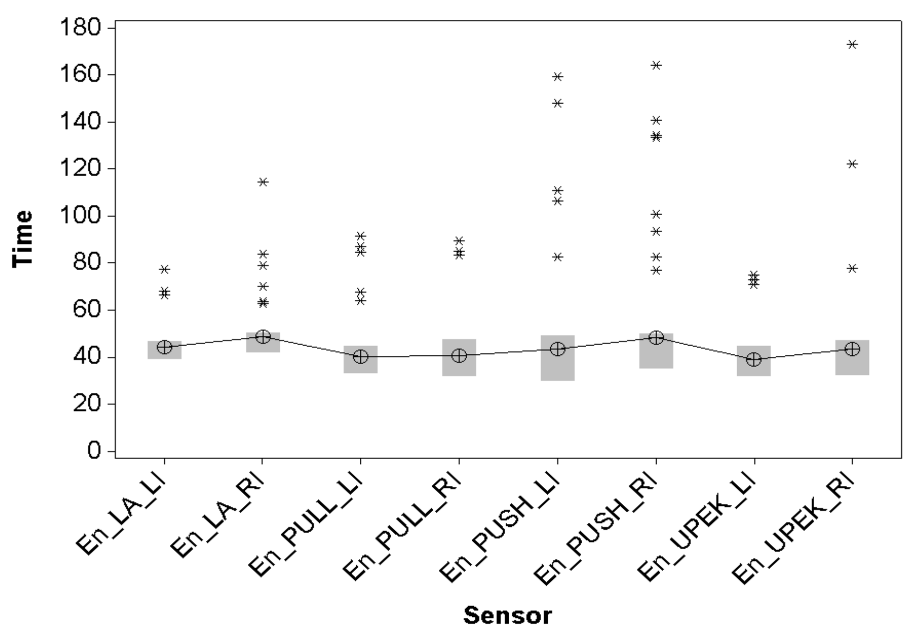


Figure 155 Box plot of enrollment task time by sensor and finger.

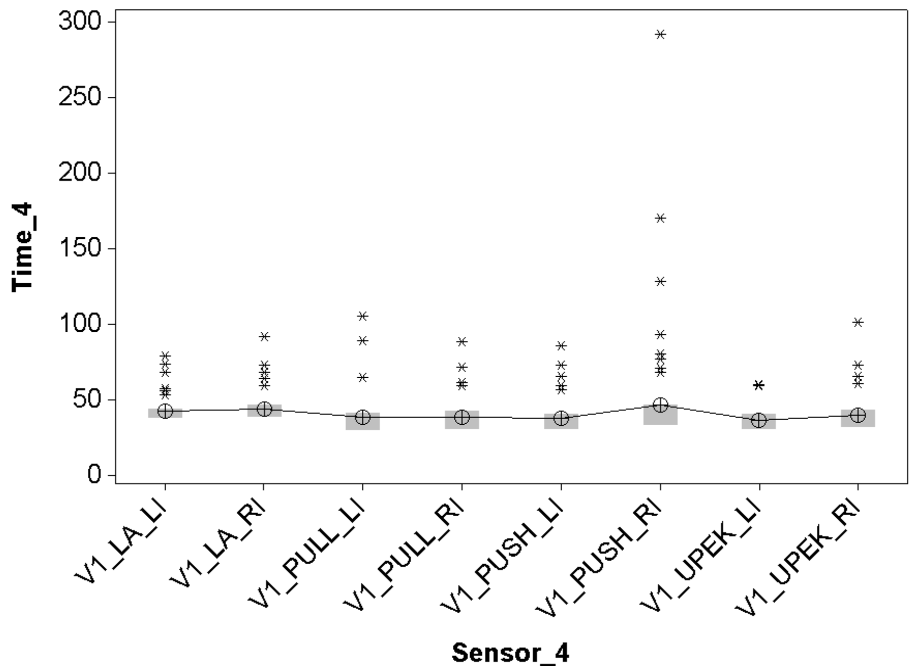


Figure 156 Box plot of matching visit 1 task time by sensor and finger.

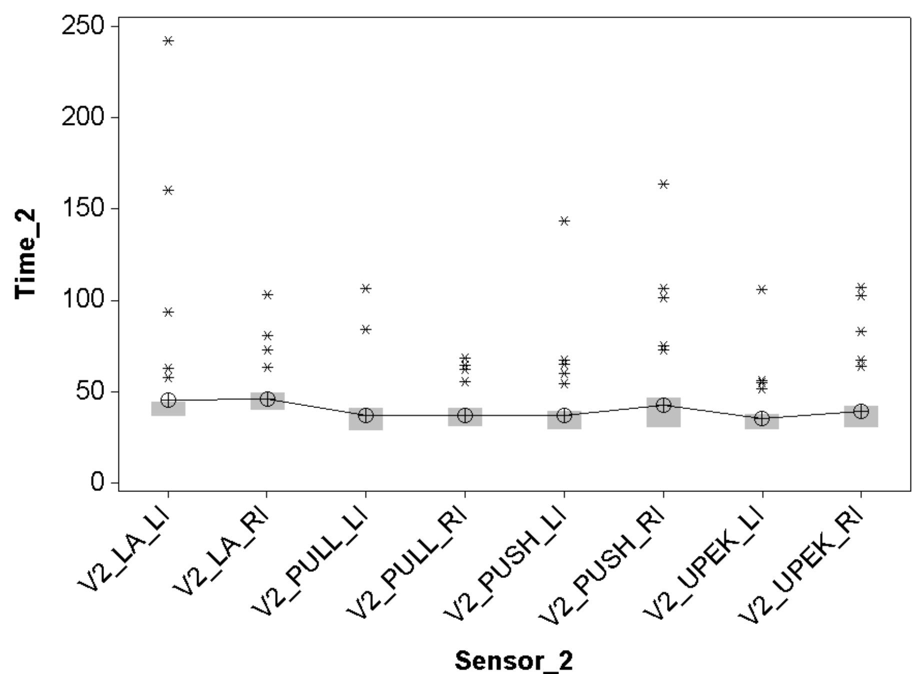


Figure 157 Box plot of matching visit 2 task time by sensor and finger.

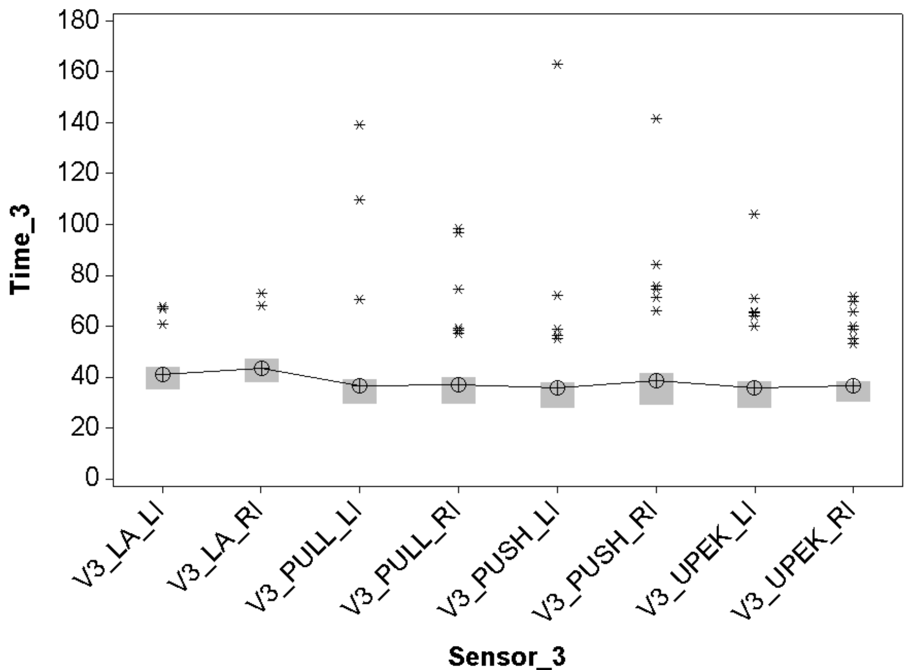


Figure 158 Box plot of matching visit 3 task time by sensor and finger.

Appendix BB. Overall FTA Additional Analyses and Results

Table 130 FTA breakdown for all interactions by sensor and finger.

	Acceptable Conformant				Unacceptable Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	3725	87.92%	3714	87.24%	339	8.00%	406	9.54%
PUSH	3606	83.11%	3653	80.22%	486	11.20%	596	13.09%
PULL	3720	85.71%	3730	90.10%	412	9.49%	329	7.95%
LA	3740	99.52%	3738	99.18%	0	0.00%	0	0.00%

	Acceptable Non-Conformant				Unacceptable Non-Conformant			
	LI		RI		LI		RI	
Sensor	N	%	N	%	N	%	N	%
UPEK	0	0.00%	0	0.00%	173	4.08%	137	3.22%
PUSH	1	0.02%	6	0.13%	246	5.67%	299	6.57%
PULL	0	0.00%	2	0.05%	208	4.79%	79	1.91%
LA	2	0.05%	2	0.05%	16	0.43%	29	0.77%

Table 131 Marascuillo procedure for comparing multiple proportions for all interactions.

	Acceptable Conformant		Unacceptable Conformant	
Sensor	LI	RI	LI	RI
PUSH	$p < .05$	$p < .05$	$p < .05$	$p < .05$
PULL	*n. s.*	$p < .05$	*n. s.*	*n. s.*
LA	$p < .05$	$p < .05$	$p < .05$	$p < .05$

	Acceptable Non-Conformant		Unacceptable Non-Conformant	
Sensor	LI	RI	LI	RI
PUSH	*n. s.*	*n. s.*	$p < .05$	$p < .05$
PULL	*n. s.*	*n. s.*	*n. s.*	$p < .05$
LA	*n. s.*	*n. s.*	$p < .05$	$p < .05$

Table 132 Acceptable non-conformant FTA breakdown by data collection component, sensor, and finger.

Data collection component	Sensor	Finger	Acceptable Non-Conformant		
			Wrong Movement	Wrong Direction	Wrong Finger
TR	PULL	RI	1	2	0
V1	PUSH	RI	0	2	0
V1	LA	LI	0	0	1
V2	LA	RI	0	0	2
V2	PUSH	LI	0	1	0

Table 133 Unacceptable non-conformant FTA breakdown for the large area sensor.

Data collection component	Sensor	Finger	Unacceptable Non-Conformant
			Swiped
TR	LA	RI	2
V2	LA	RI	5
V3	LA	RI	5

Appendix CC. Matching Performance DETs by Data Collection Component

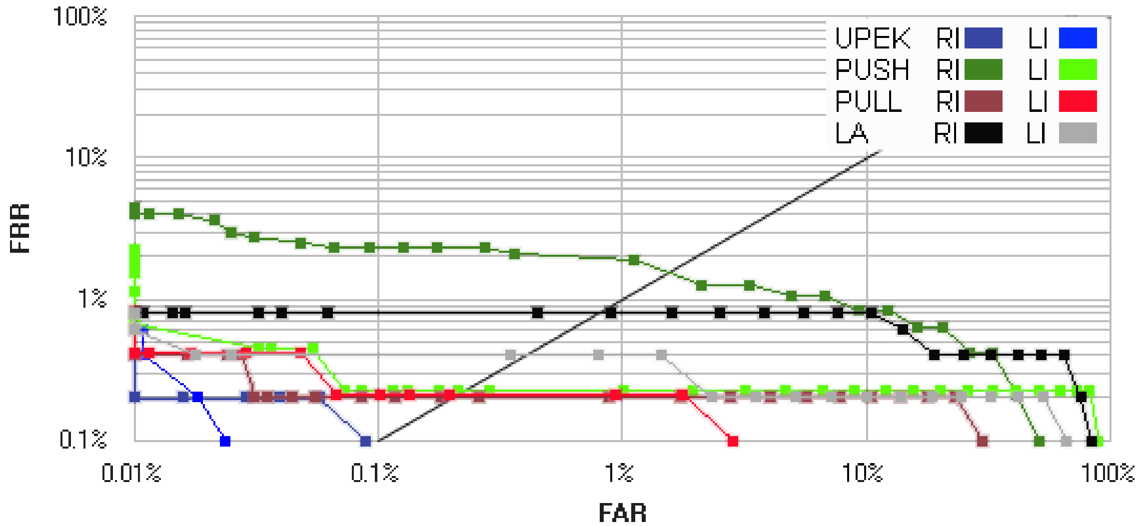


Figure 159 DET for training for each sensor and finger.

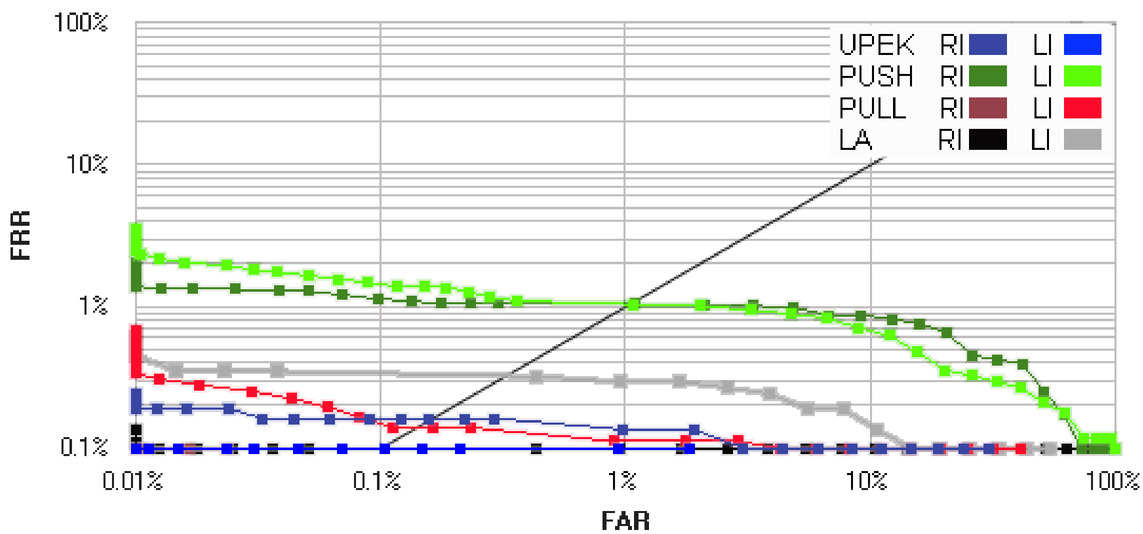


Figure 160 DET for enrollment for each sensor and finger.

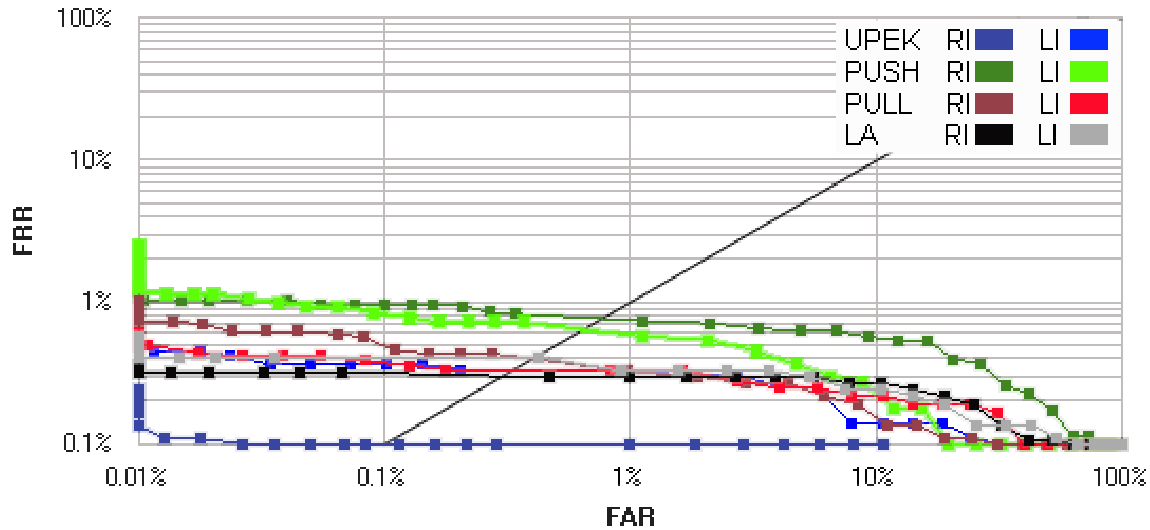


Figure 161 DET for matching visit 1 for each sensor and finger.

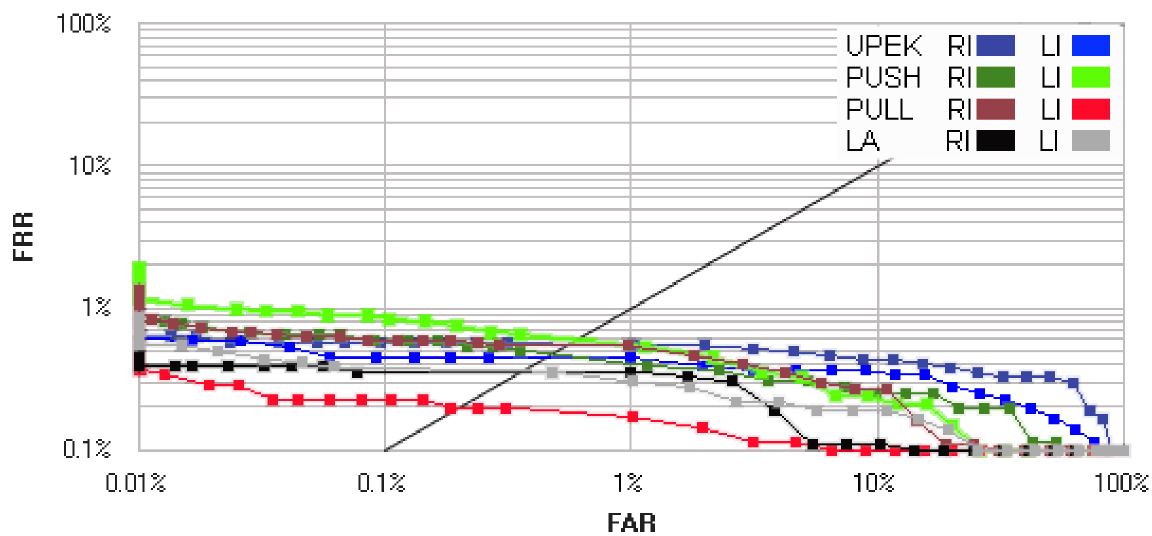


Figure 162 DET for matching visit 2 for each sensor and finger.

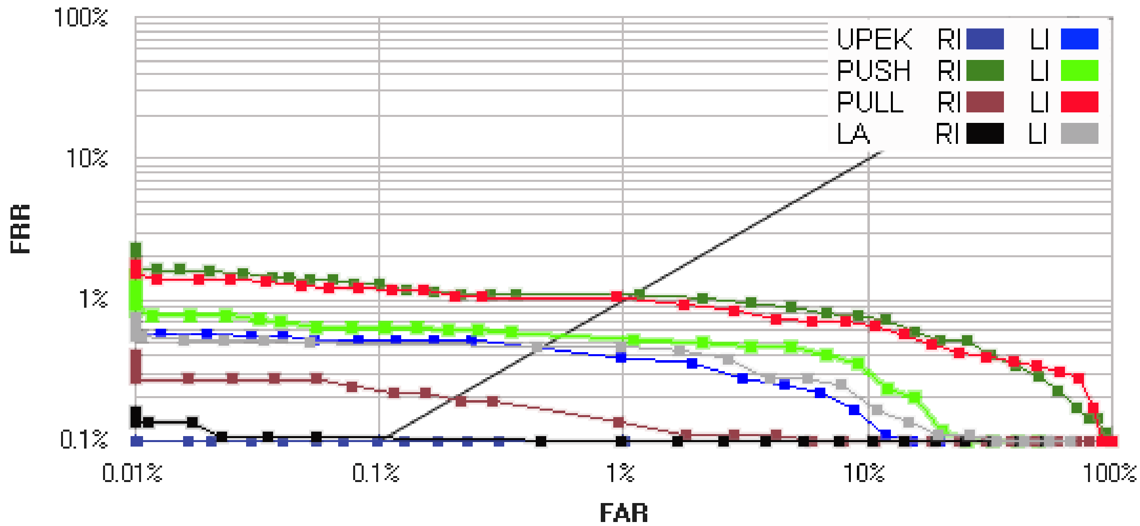


Figure 163 DET for matching visit 3 for each sensor and finger.

Appendix DD. Matching Performance DETs by Sensor

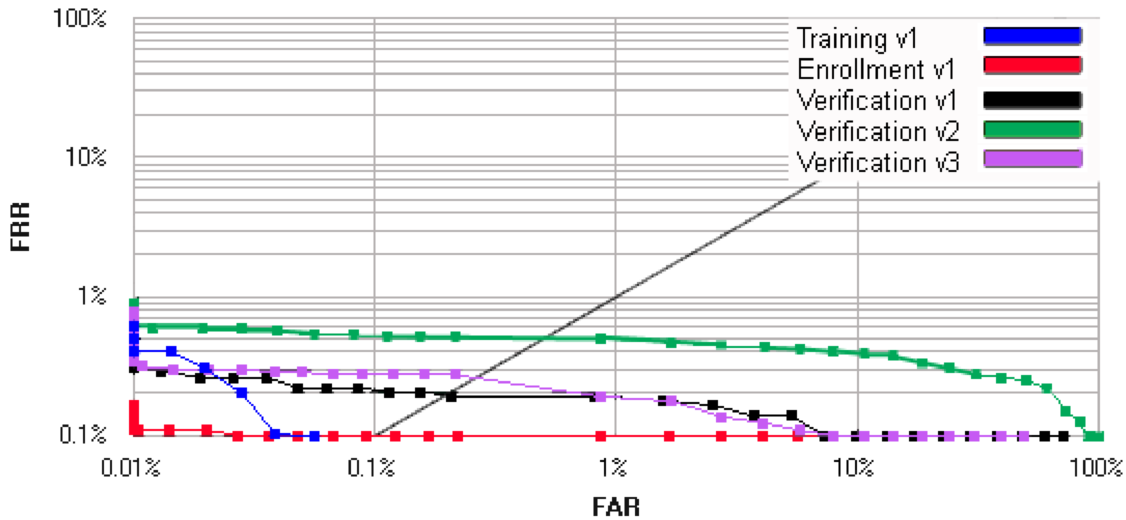


Figure 164 DET for the UPEK sensor by data collection component.

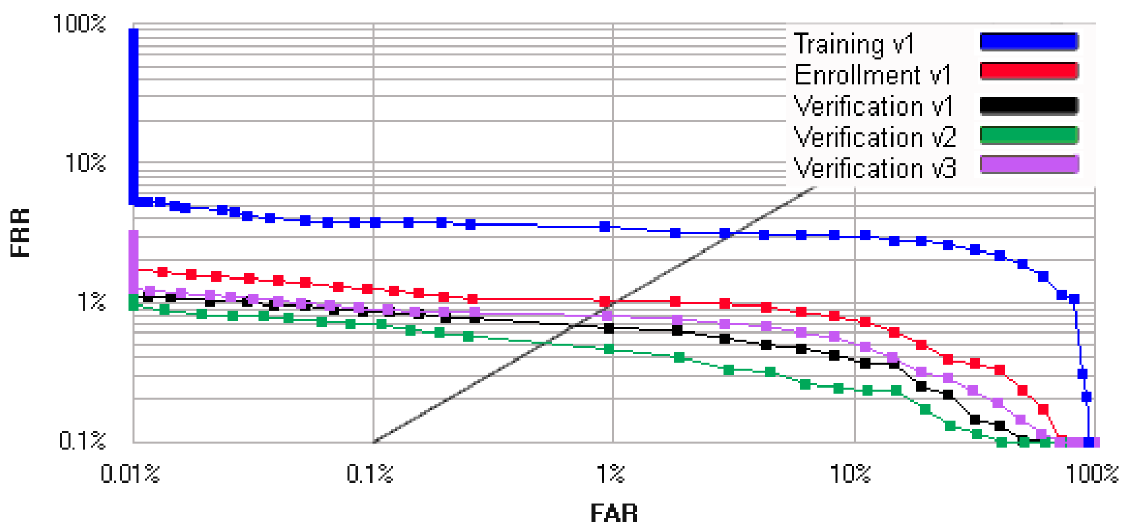


Figure 165 DET for the PUSH sensor by data collection component.

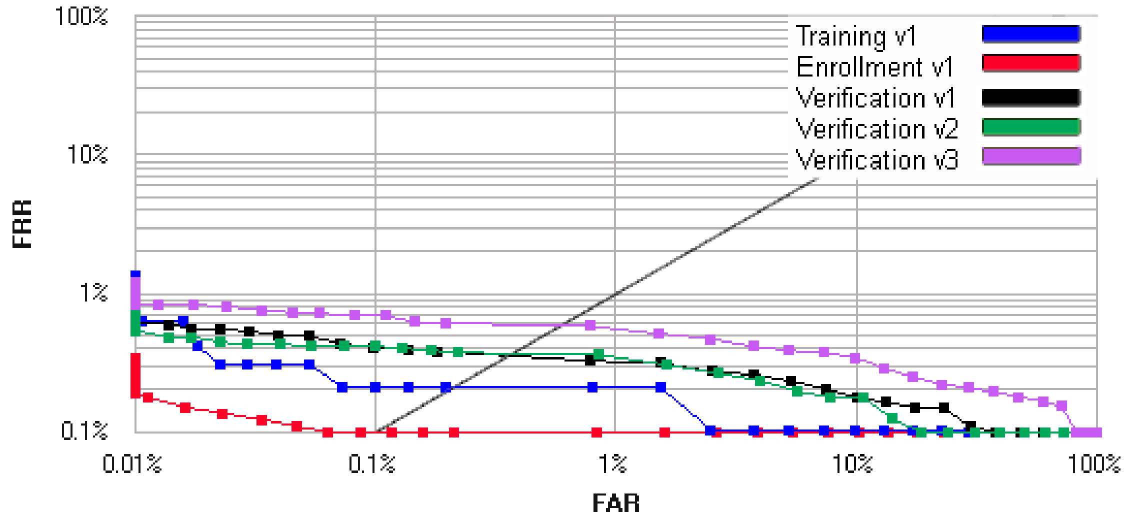


Figure 166 DET for the PULL sensor by data collection component.

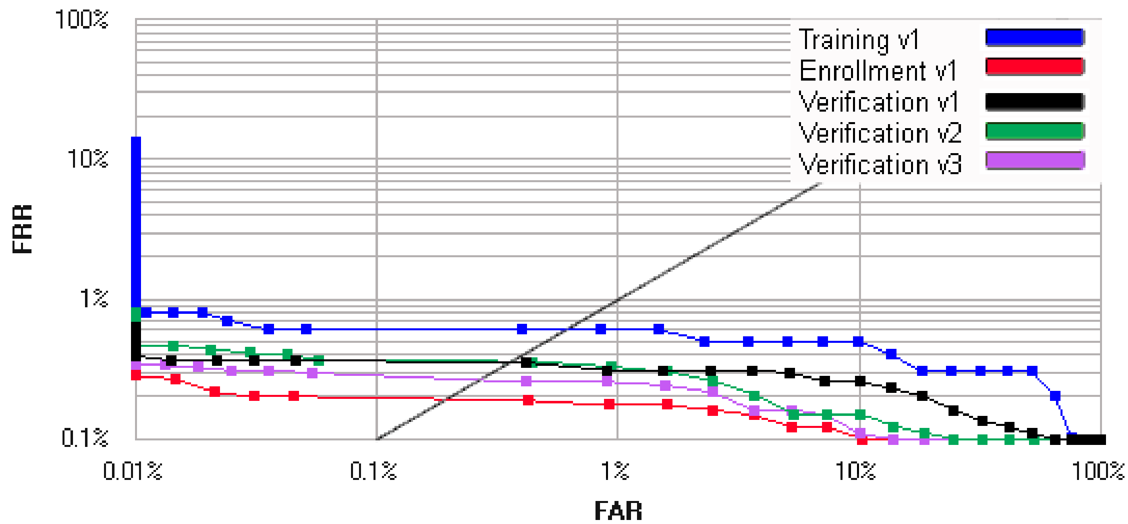


Figure 167 DET for the Large Area sensor by data collection component.

VITA

VITA

Educational Background

B.S.	Industrial Distribution, Minor in Management, Purdue University	2002
M.S.	Technology, Specialization: Information Security, Purdue University Thesis: The Effects of Varying Illumination Levels on FRS Algorithm Performance: *Stephen J. Elliott, Ph.D., advisor*	2004
Ph.D.	Technology, Specialization: Computational Science, Purdue University Dissertation: Design and Evaluation of the Human-Biometric Sensor Interaction Method: *Stephen J. Elliott, Ph.D., advisor*	2008

Academic Appointments

a. Teaching appointments

(1)	2006 - 2008	Purdue University Discovery Learning Center / National Science Foundation Graduate Teaching Fellow in GK-12 Education
(2)	2005 – 2006	Purdue University Graduate School Strategic Initiatives Fellow
(3)	2003 – 2005	Purdue University Industrial Technology Teaching Assistant

b. Laboratory or research appointments

(1)	2003 – 2008	Purdue University Biometrics Standards, Performance, & Assurance Laboratory Researcher

Industrial, business, and governmental experience

a.	2003 – present	InterNational Committee for Information Technology Standards (INCITS) Technical Committee M1 Biometrics Member of Technical Group M1.5: Biometric Performance Testing and Reporting

b. 2004 – present International Organization for Standardization (ISO/IEC) Joint Technical Committee (JTC) 1 Sub Committee (SC) 37 U.S. Technical Expert for WG5: Biometric Testing and Reporting

Awards and honors

a. 2008 Best Research Poster Award
9th Annual Center for Education and Research in Information Assurance and Security (CERIAS) Information Security Symposium, March 18, 2008
Purdue University

b. 2004 – 2005 Graduate Student Award for Outstanding Teaching
Industrial Technology Department,
Purdue University

c. 2003 – 2004 Outstanding Graduate Student Award
School of Technology,
Purdue University

Refereed or reviewed publications

a. Chapters in internationally published books

(1) Kukula, E., & Elliott, S. (submitted). Biometric System Ergonomic Design. In S. Li (Ed.), *Encyclopedia of Biometrics.* Springer. pp. 1000. ISBN 978-0-387-73002-8. (to be published May 2009).

(2) Elliott, S., Kukula, E., & Modi, S. (2007). Issues Involving the Human Biometric Sensor Interface. In S. Yanushkevich, P. Wang, & S. Srihari (Eds.), *Image Pattern Recognition: Synthesis and Analysis in Biometrics*. World Scientific Publishers. Series in Machine Perception and Artificial Intelligence. vol. 67. 339-364. ISBN: 978-981-256-908-0.

b. Refereed journal articles

(1) Elliott, S. J. & Kukula, E.P. (2007). The Challenges Associated with Laboratory-Based Distance Education. *EDUCAUSE Quarterly*. *Vol 30* (1). 37-42

(2) Kukula, E. P, & Elliott, S. J. (2006). Implementation of hand geometry: An analysis of user perspectives and system performance. *IEEE Aerospace and Electronic Systems Magazine*. *Vol 21* (3), March 2006. 3-9.

(3) Kukula, E. P, & Elliott, S. J. (2004). Evaluation of a Facial Recognition Algorithm Across Three Illumination Conditions*. IEEE Aerospace and Electronic Systems Magazine*. *Vol 19* (9). 19-23.

c. Refereed conference proceedings (with presentation)

(1) Kukula, E.*, Blomeke, C., Modi, S., & Elliott, S. (2008). Effect of Human Interaction on Fingerprint Matching Performance, Image Quality, and Minutiae Count. (771-776). *Proceedings of the 5th International Conference on Information Technology and Applications (ICITA 2008). Cairns, Australia.* ISBN: 978-0-9803267-2-7.

(2) Modi, S., Elliott, S., Kim, H., & Kukula, E.* (2008). Statistical Analysis Framework for Biometric System Interoperability Testing. (777-782). *Proceedings of the 5th International Conference on Information Technology and Applications (ICITA 2008). Cairns, Australia.* ISBN: 978-0-9803267-2-7.

(3) Frick, M.*, Modi, S., Elliott, S., & Kukula, E. (2008). Impact of Gender on Fingerprint Recognition Systems. (717-721). *Proceedings of the 5th International Conference on Information Technology and Applications (ICITA 2008). Cairns, Australia.* ISBN: 978-0-9803267-2-7.

(4) Kukula, E.*, Elliott, S., & Duffy, V. (2007). The Effects of Human Interaction on Biometric System Performance. (903-913). *Proceedings of the 12th International Conference on Human-Computer Interaction and 1st International Conference on Digital-Human Modeling*. *Beijing, China*, Springer-Verlag. LNCS 4561. ISBN 978-3-540-73318-8.

(5) Kukula, E.*, Elliott, S., Gresock, B., & Dunning, N. (2007). Defining Habituation using Hand Geometry. (242-246). *Proceedings of the 5th IEEE Workshop on Automatic Identification Advanced Technologies. Alghero, Italy.* ISBN: 1-4244-1300-1.

(6) Kukula, E.*, Elliott, S., Kim, H., & San Martin, C. (2007). The Impact of Fingerprint Force on Image Quality and the Detection of Minutiae. (432-437). *Proceedings of the 2007 IEEE International Conference on Electro/Information Technology (EIT)*. *Chicago, IL*. ISBN: 978-1-4244-0941-9.

(7) Kukula, E.* & Elliott, S. (2006). Implementing Ergonomic Principles in a Biometric System: A Look at the Human Biometric Sensor Interaction. (86-91). *Proceedings of the 40th IEEE International Carnahan Conference on Security Technology (ICCST). Lexington, KY.* ISBN: 1-4244-0174-7.

(8) Elliott, S. J., & Kukula, E. P.* (2006). The Evolution and Enhancement of a Graduate Course in Biometrics. (89-92) *World Congress on Computer Science, Engineering, and Technology Education (WCCSETE)*, *Santos, Brazil.* ISBN: 85-89120-30-9.

(9) Elliott, S. J.*, Kukula, E. P., & Sickler, N. C. (2006). An Assessment of Performance Between On- and Off Campus Students in an Automatic Identification and Data Capture Course, (93-96). *World Congress on Computer Science, Engineering, and Technology Education (WCCSETE)*, *Santos, Brazil.* ISBN: 85-89120-30-9.

(10) Kukula, E. P.*, & Elliott, S. J. (2005). Implementation of hand geometry at Purdue University's Recreational Center. An analysis of user perspectives and system performance. (83-88). *Proceedings of the 39th Annual International Carnahan Conference on Security Technology (ICCST).* Las Palmas de G. C., Spain. ISBN: 0-7803-9245-0.

(11) Kukula, E. P.*, & Elliott, S.J. (2004). Effects of Illumination Changes on the Performance of Geometrix FaceVision 3D FRS. (331-337). *Proceedings of the 38th Annual 2004 International Carnahan Conference on Security Technology (ICCST)*. *Albuquerque, New Mexico.* ISBN: 0-7803-8506-3.

(12) Elliott, S. J.*, Kukula, E. P., & Sickler, N. C., (2004). *The Challenges of the Environment and the Human / Biometric Device Interaction on Biometric System Performance*, International Workshop on Biometric Technologies-Special forum on Modeling and Simulation in Biometric Technology, Calgary, Alberta, Canada

(13) Kukula, E.P., Sickler, N.C., & Elliott, S.J. (2004, March 14-17). *Adaptation and Implementation to a Graduate Course Development in Biometrics.* Paper presented at the World Congress on Engineering and Technology Education (WCETE), Santos, Brazil

(14) Sickler, N.C., Kukula, E.P., & Elliott, S.J. (2004, March 14-17). *Using Web-Based Tools to Enhance Students Learning in the Field of Automatic Identification and Data Capture.* Paper presented at the World Congress on Engineering and Technology Education (WCETE), Santos, Brazil

(15) Kukula, E.P.*, & Elliott, S.J. (2003, October 14 - 16). *Securing a Restricted Site: Biometric Authentication at Entry Point.* Paper presented at the 37th Annual 2003 International Carnahan Conference on Security Technology (ICCST), pp. 435-439, Taipei, Taiwan, ROC

(16) Morton, J., Portell, C., Elliott, S., & Kukula, E.* (2003, October 14 - 16). *Facial Recognition at Purdue University's Airport 2003-2008.* Paper presented at the 37th Annual 2003 International Carnahan Conference on Security Technology (ICCST), pp.531-534, Taipei, Taiwan, ROC

d. Conference presentations (online proceedings)

(1) Kukula, E. P.* (2007, November 7-8). *Understanding the Impact of the Human-Biometric Sensor Interaction and System Design on Biometric Image Quality.* Paper presented at the NIST Biometric Quality Workshop II, Gaithersburg, MD, from HTTP://WWW.ITL.NIST.GOV/IAD/894.03/QUALITY/WORKSHOP07/INDEX.HTML

(2) Kukula, E. P.* (2004, September 19 – 22). *Effects of Light Direction on the Performance of Geometrix FaceVision 3D Face Recognition System.* Paper presented at the Biometric Consortium, Hyatt Regency Washington, D.C., from HTTP://WWW.BIOMETRICS.ORG/BC2004/PROGRAM.HTM

(3) Kukula, E.P.*, & Elliott, S.J. (2003). *Securing a Restricted Site: Biometric Authentication at Entry Point.* Paper presented at the Biometric Consortium - Biometric Symposium on Research, Hyatt Regency Washington, D.C., from HTTP://WWW.BIOMETRICS.ORG/BC2003/PROGRAM.HTM

d. Other scholarly publications related to teaching (Locally published textbooks)

(1) Elliott, S.J., Sickler, N.C., & Kukula, E.P. (2005). Automatic Identification and Data Capture. Ed3. Copymat. pp. 314

(2) Elliott, S.J., Sickler, N.C., Kukula, E.P., & Modi, S.K. (2005). From Bar Codes to Biometrics: What the Practitioner Needs to Know. Copymat. pp 447.

(3) Elliott, S.J., Sickler, N.C., & Kukula, E.P. (2004). Automatic Identification and Data Capture. Ed2. Copymat. pp. 317.

(4) Elliott, S.J., Sickler, N.C., Kukula, E.P., & Modi, S.K. (2004). Introduction to Biometric Technology. Copymat. pp. 184.

e. Poster presentations

(1) Kukula, E., Elliott. S., Sutton, M., Latif, N., & Duffy, V. (2008, March 18). Design & Evaluation of the Human-Biometric Sensor Interaction (HBSI) Method. Presented at the 9th Annual Center for Education and Research in Information Assurance and Security (CERIAS) Information Security Symposium, West Lafayette, IN. *Awarded Best Research Poster*.

(2) Kukula, E. P., & Elliott, S. J., (2008, February 23). Design and Evaluation of the Human-Biometric Sensor Interaction Method, College of Technology Faculty Convocation, West Lafayette, IN

(3) Kukula, E., Elliott, S., Gresock, B., and Dunning, N. (2007, June 7-8). Defining Habituation using Hand Geometry. Presented at the 5th IEEE Workshop on Automatic Identification Advanced Technologies in Alghero, Italy.

(4) Kukula, E. and Elliott. S. (2007, March 20-21). The Effects of Human Interaction on Biometric System Performance. Presented at the 2007 Annual Center for Education and Research in Information Assurance and Security (CERIAS) Information Security Symposium, West Lafayette, IN.
(5) Kukula, E., Menon, A., Dark, M., and Elliott S. (2007, March 9-11). Face Recognition & Misidentification: Using the fellow's research to examine the scientific method & measurements of central tendency. Poster presented at the 7th Annual NSF Graduate Teaching Fellows in K-12 Education (GK-12) Project Meeting. Washington DC
(6) Kukula, E. and Elliott. S. (2007, March 9). The Effects of Human Interaction on Biometric System Performance. Presented at the National Science Foundation’s Poster Session of Graduate Teaching Fellows in K-12 Education Program. Arlington, VA.
(7) Kukula, E. P., & Elliott, S. J., (2006). Critical Anthropometric & Ergonomic Elements for Reliable Hand Placement in Hand Geometry Based Authentication System, Center for Education and Research in Information Assurance and Security "Security in Motion" Symposium, West Lafayette, IN.
(8) Kukula, E. P. (2006). Critical Anthropometric & Ergonomic Elements for Reliable Hand Placement in Hand Geometry Based Authentication System, Poster No E-12, Purdue University Chapter, The Society of Sigma Xi Graduate Student Research Poster Competition, West Lafayette, IN.
(9) Kukula, E. P., & Elliott, S. J., (2006). Standards Work in Multimodal & Other Multibiometric Fusion, College of Technology Faculty Convocation, West Lafayette, IN
(10) Kukula, E. P. & Elliott, S. J., (2005). Biometric Feasibility Study: Hand Geometry at the Recreational Sports Center, Center for Education and Research in Information Assurance and Security "Security in Motion" Symposium, West Lafayette, IN.
(11) Kukula*, E. P., & Elliott, S. J. (2003). Securing a Restricted Site: Biometric authentication at an entry point. Center for Education and Research in Information Assurance and Security Symposium, West Lafayette, IN.

American National Standards

a. Technical Report

(1) Kukula, E., Elliott, S., & Tilton, C. (co-editors), “ANSI Technical Report – Information technology – Biometric Performance Testing and Reporting – Part 7: Framework for Testing Methodologies for Specific Modalities,” Committee Draft Status, April 11, 2008.

Patents

a. Provisional (active)

(1) Kukula, E., Modi, S., & Elliott, S., "Improved Fingerprint Acquisition System and Method Using Force Measurements," U.S. Provisional Patent Application 65047.PI.US, February 29, 2008.

b. Provisional (expired)

(1) Elliott, S. J., Kukula, E. P., Modi, S. K., Sickler, N. C., "Communicating Secret Messages To A Machine Using a Biometric Trait," U.S. Provisional Patent Application Ref No. P04088.PI.US, July 16, 2004.

(2) Elliott, S. J., Modi, S. K., Kukula, E. P., Sickler, N. C., "Authenticating Individuals Using Key Press Dynamics," U.S. Provisional Patent Application Ref No. P04054.PI.US, July 20, 2004.

Professional Activities

a. Conference Session Chair

(1) "Biomedical System and Bioinformatics III," 2008 IEEE 5th International Conference on Information Technology and Applications (ICITA). Cairns, Australia. June 24 – 26, 2008.

Invited presentations, lectures, or talks presented at meetings of educational societies, conferences, other educational institutions, or in the community

a. Regional

2006 Introduction to Biometric Technologies", Invited Lab Instructor, 2006 Automatic Identification & Data Capture Technical Institute (AIDCTI), July 24-27, 2006, Ohio University, Athens, OH.

2005 "An Overview of Biometrics", Invited Lecturer and Lab Instructor, 2005 Automatic Identification & Data Capture Technical Institute (AIDCTI), July 24-29, 2005, Ohio University, Athens, OH

2004 "Biometric Technologies", Invited Lab Instructor, 2004 Automatic Identification & Data Capture Technical Institute (AIDCTI), July 26-29, 2004, Ohio University, Athens, OH.

b. Local

2008 "Biometrics Research in the GK-12 Environment", Purdue University Indiana Interdisciplinary GK-12 Program In-Service Meeting, April 11, 2008, Purdue University, West Lafayette, IN

2007 "How in the whorl-d can you identify me? A Lesson in Biometrics", Windows of Opportunity for Women in Technology (WOW) Program., November 4, 2007, Purdue University, West Lafayette, IN

2007 "Biometrics & Homeland Security", ASM 591B - Foundations in Homeland Security Studies II, April 3, 2007, Purdue University, West Lafayette, IN

2007 "Biometrics and Issues Users Face", IE 486 - Work Analysis & Design, March 30, 2007, Purdue University, West Lafayette, IN

2007 "Biometrics - Those cool gadgets you see on TV...", Vision Program, March 29, 2007, Purdue University, West Lafayette, IN

2007 "Biometrics - Those cool gadgets you see on TV...,", Discovering Opportunities in Technology Program (DO IT!), March 1, 2007, Purdue University, West Lafayette, IN

2007 "Biometric Deployments and Observations", IT 345 - Automatic Identification & Data Capture, February 7, 2007, Purdue University, West Lafayette, IN

2007 "Hand Geometry", IT 345 - Automatic Identification & Data Capture, January 26, 2007, Purdue University, West Lafayette, IN

2007 "Face Recognition", IT 345 - Automatic Identification & Data Capture, January 26, 2007, Purdue University, West Lafayette, IN'

2007 "Biometrics & Ergonomics", IT 345 - Automatic Identification & Data Capture, January 24, 2007, Purdue University, West Lafayette, IN

2007 "Physical Security and Authentication", IT 560W – Manufacturing and Supply Chain Security, January 20, 2007, Purdue University, West Lafayette, IN

2006 "Am I a Scientist?", Presented to 8th Grade Science Students at Tecumseh Junior High School, August 29, 2006, Lafayette, IN

2006 "Biometrics. What is it?", Technology Advances Girl Scouts (TAGS) Camp, July 18, 2006, Purdue University, West Lafayette, IN

2005 Biometrics…. Bio-what???, Turned on to Technology and Leadership (TOTAL) Summer Camp, June 13, 2005, Purdue University, West Lafayette, IN

2005 "Biometrics…. Bio-what???", Minority Technology Association (MTA) Vision Program, March 25, 2005, Purdue University, West Lafayette, IN

2004 "Overview of Biometrics", High School Seniors in Technology Camp, June 29, 2004, Purdue University, West Lafayette, IN

2004 "An Overview of Biometrics," for the Minority Engineering Program (MEP) Summer Engineering Workshop, June 10, 2004, Purdue University, West Lafayette, IN

Service and Engagement

a. University committee membership

(1) 2003-04 Purdue University Grade Appeals Committee

b. Professional Organizations / Associations

(1) 2003-08 InterNational Committee for Information Technology Standards (INCITS)

(2) 2003-08 Institute of Electrical and Electronics Engineers (IEEE)

(3) 2003-08 Human Factors and Ergonomic Society (HFES)

(4) 2001-07 National Association of Industrial Technology (NAIT)