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Learning Opportunities and Challenges of Sensor-enabled Intelligent Tutoring Systems on Mobile Platforms: Benchmarking the Reliability of Mobile Sensors to Track Human Physiological Signals and Behaviors to Enhance Tablet-Based Intelligent Tutoring Systems

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LEARNING OPPORTUNITIES AND CHALLENGES OF SENSOR-ENABLED
INTELLIGENT TUTORING SYSTEMS ON MOBILE PLATFORMS:
BENCHMARKING THE RELIABILITY OF MOBILE SENSORS TO TRACK
HUMAN PHYSIOLOGICAL SIGNALS AND BEHAVIORS TO ENHANCE TABLET-
BASED INTELLIGENT TUTORING SYSTEMS

by

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ABSTRACT

Desktop-based intelligent tutoring systems have existed for many decades, but the advancement of mobile computing technologies has sparked interest in developing mobile intelligent tutoring systems (mITS). Personalized mITS are applicable to not only stand-alone and client-server systems but also cloud systems possibly leveraging big data. Device-based sensors enable even greater personalization through capture of physiological signals during periods of student study. However, personalizing mITS to individual students faces challenges. The Achilles heel of personalization is the feasibility and reliability of these sensors to accurately capture physiological signals and behavior measures.

This research reviews feasibility and benchmarks reliability of basic mobile platform sensors in various student postures. The research software and methodology are generalizable to a range of platforms and sensors. Incorporating the tile-based puzzle game 2048 as a substitute for a knowledge domain also enables a broad spectrum of test populations. Baseline sensors include the on-board camera to detect eyes/faces and the Bluetooth Empatica E4 wristband to capture heart rate, electrodermal activity (EDA), and skin temperature. The test population involved 100 collegiate students randomly assigned to one of three different ergonomic positions in a classroom: sitting at a table, standing at a counter, or reclining on a sofa. Well received by the students, EDA proved to be more reliable than heart rate or face detection in the three different ergonomic

positions. Additional insights are provided on advancing learning personalization

through future sensor feasibility and reliability studies.

"You aren't going to find anybody that's going to be successful without making a sacrifice and without perseverance." -Lou Holtz

This dissertation is dedicated to my wife, Katherine, and two children, Juliana and Jacob. Their sacrifice and patience during this long endeavor proves anything worth doing is hard, but not impossible if you overcome the obstacles, continue making progress, and follow your dreams.

ACKNOWLEDGMENTS

Lastly, I want to thank my grandmother, Aida, and my late grandfather, Gilberto, who worked extremely hard to secure safe passage into the United States and support the family as they established a new way of life. At a very young age, they always instilled the importance of education within me, and inspired me to challenge myself educationally. I have achieved many of the "firsts" within our family: first bachelor's degree, first master's degree, and finally, first dissertation, but without the sacrifice and educational priorities laid by my grandparents, these "firsts" would not have occurred. I hope others in the family continue taking similar steps to keep the momentum of making new family "firsts."

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CHAPTER ONE: INTRODUCTION

Intelligent Tutoring Systems are effective instructional platforms that have primarily delivered instruction through desktop computer hardware augmented by a variety of sensors. Increasingly, desktop computer users are migrating to mobile platforms (Gartner, 2018) and it is our goal to facilitate the migration of these intelligent tutoring systems to mobile platforms, such as tablets. The research described herein examines sensor technologies and the efficacy of their transfer from desktop to mobile instructional platforms.

Mobile Computing Platforms

With the advancement of mobile computing technologies, communication networks, and social platforms, people have forged a relationship which seems impossible to imagine modern life without these additions. From these tools and innovations, there is a strong motivation to automate and/or migrate everything into a 'mobile' package. In a general sense, mobile is the concept where an individual is not constrained to one location and is free to move around. This idea is then applied to computing hardware, software, and the necessary infrastructure which supports this unfettered lifestyle, such as phones, tablets, operating systems, software, and communication protocols.

As a background, mobile phones are handheld devices that connects to a cellular network that is able to communicate with the Internet and run specialized applications. Similarly, tablets also connect to the Internet and run specialized applications (via a cellular network and/or 802.11 wireless networks) but possess larger screens. Even though tablet

computing has grown in popularity over the past few years, it isn't a new idea.

Moreover, early signs of tablets can be traced back to a patent submitted in 1888 which

was a system that was used in handwriting recognition (386815, 1888). However, from

the early days of computing, tablets have been associated with the use of a digital pen or

stylus, as it's evident from patents published and systems developed in the early 1900s

throughout the 1950s (1117184, 1914) (Dimond, 1957) and continues through today.

Modern tablets (or tablet PCs) can be seen to have its origins in touch-input hardware

development in the mid-1960s (Schedeen, 2010). These tablets relied heavily on the use

of a stylus in order to digitize input to be consumed by the system (Schedeen, 2010). As

computing technology improved, the tablet also became lighter, smaller, and more

portable (Schedeen, 2010). Over the past few years, hardware manufacturers have come

up with combinations of devices that blends the tablet and laptop, commonly referred to

as "convertibles", "detachables", and "sliders" (Spoonauer, 2013). These terms stem

from the action these devices possess any of the following qualities: convert between

laptops and tablets or detachable/slidable keyboards. With respect to this research, a

tablet is a mobile device, with a touch-sensitive area with a diagonal size of at least seven

inches. The tablet definition will apply to devices such as the Nexus 7, Surface, and iPad.

However, the audience for tablets did not materialize until the commercialization of

multi-touch technology incorporated in products such as the iPhone and iPad (Schedeen,

2010) between 2007 and 2010. The iPad allows for a comfortable replacement for

laptops and desktop computers for browsing web content such as news and social media

sites and for casual gaming (Griffey, 2012). With the popularization of the mobile tablet

for consumer use, the tablet has also been applied to various different fields with some examples in: education (Leonard, 2013), medicine (Glaser, Jain, & Kortum, 2013), and business (Dalenberg, 2012).

In order to put into perspective how fast the mobile platform is expanding, annual sales for smartphones grew from 122.32 million units in 2007 to 1.536 billion units in 2017 (Statista, 2018a). Although not as dramatic, tablets grew annual sales from 76 million units in 2011 to 163.7 million units in 2017 (Statista, 2018b). Although the sales of phones and tablets are growing at different rates, their sales are expected to continue to grow for the foreseeable future (Gartner, 2018). Furthermore, these mobile computing technologies (smartphones and tablets) has even outpaced the sales of traditional desktop computers (Gartner, 2018). Moreover, Statista (2018a, 2018b) presents data that laptops have been sold more than their desktop counterparts over the past decade and smartphones have exceeded them both. According to Gartner in 2014, there is a direct correlation between the decline of desktops and the rise of mobile devices as users reduce their use of desktops and laptops in order to take advantage of the "flexibility" that a mobile computing device offers (Gartner, 2014). With the growing sales of mobile computing products, the idea is reinforced that more people will have ample computational resources anywhere they go (Ba, Heinzelman, Janssen, & Shi, 2013).

Nonetheless, having almost half a billion smartphones sold in one year (Ba et al., 2013) isn't as significant, until we start to leverage the power of the internet and connect them all together. This allows for these owners to harness the wealth of information that can be found on the internet, without the requirement of being chained to a stationary desktop

computer. The demand imposed by these devices starts to bog down wireless

telecommunication networks such as 2G, 3G and 4G across the globe (Cisco, 2013).

According to a study conducted by the Cisco Visual Networking Index (VNI) team, data

usage (or traffic) on mobile networks increased by 70% in 2012 (Cisco, 2013).

Moreover, if it weren't for the increased usage of Wi-Fi networks to divert mobile data

traffic away from telecommunication networks, the bandwidth for the wireless

telecommunication networks would be even worse (Cisco, 2013). This study predicts

mobile traffic will also continue to rise while the bandwidth and speeds of these mobile

networks will similarly improve (Cisco, 2013). Moreover, the Cisco VNI team points out

the majority of the mobile traffic comes directly from the use of specialized software

applications designed to be used on a mobile operating system, such as Android and iOS

(Cisco, 2013). These mobile platform applications, or "apps", can be seen as the

influential driver behind the growth in mobile computing sales and global mobile

network data traffic, which in turn pushes telecommunication companies to upgrade their

infrastructure to support this increasing demand.

Learning applications have not been absent from the mobile computing platform and

researchers have been investigating the benefits of using the mobile platform for

educational purposes (Wu et al., 2012). From the meta-analysis performed by Wu et al.

in 2012, research on learning using a mobile platform is either trying to investigate the

effectiveness and usefulness of mobile learning, and the actual act of putting together

systems that incorporate this research. Furthermore, from the 164 studies observed, 32%

of them dealt exclusively with the design of some type of mobile learning system (Wu et

al., 2012). For example, one study shows how an undergraduate engineering course included the use of a tablet pc to increase the level of student engagement (Koile & Singer, 2006).

In the study performed by Koile and Singer, the specific hardware used was not explained, but the generic "Tablet PC" term in 2006 refers to a laptop computer that has an output that allows for touch input, primarily with a stylus (Block, 2007). With this tablet PC, the instructor was able to annotate slides, and obtain digitized diagrams submitted from students' tablet PCs (Koile & Singer, 2006). From the students' feedback, the instructor is then able to tailor the instruction specifically to the current needs of the students (Koile & Singer, 2006). Another study conducted by Furió, Juan, Seguí, and Vivó (2015) showed that an iPhone educational game provided no statistical difference in knowledge retained versus those that were given traditional classroom instruction. Their findings show that an effective mobile game with a goal to teach can support and be used interchangeably with traditional classroom instruction (Furió et al., 2015). Finally, based upon student feedback, there is statistical evidence of increased student motivation and engagement if traditional classroom instruction were supplemented with mobile technology (Benham, Carvalho, & Cassens, 2014).

<div align="center">Cloud-Based Computing</div>

The pervasiveness of mobile computing has led to the popularization of the concept of clouds and cloud-based computing. Cloud is the abstract concept of having data and services residing somewhere out in a network. In 2011, the National Institute of

Standards and Technology formally defined cloud-based computing as a "model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g. networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction (Mell & Grance, 2011)." Furthermore, the definition is expanded to describe that clouds can exist in different deployment domains: private, community, public, or a hybrid, and can provide software, a computing platform, or computing infrastructure (Mell & Grance, 2011).

In other words, "cloud" can be private and be inaccessible from outside the private network, or it can be public and be accessible from just about anywhere. A good example of a private cloud is a company intranet which only services the needs of that specific company. The company intranet would be inaccessible from the public and would require a network connection within the organization.

Cloud-based computing is the idea that both data and services are available whenever they are needed from anywhere. The goal is to move the computation and storage away from the client device and into a group of powerful computers on the network (Leavitt, 2009). By offloading the processing and data from the client device, such as laptops, tablets, and mobile phones, these devices would not require advanced technical hardware. Hence, offloading processing would lead to these devices becoming almost disposable since even the information is being maintained in data repositories such as Google Drive, Dropbox, and Microsoft OneDrive.

With the growth of the cloud computing platform, numerous companies have found

success in providing cloud-based platforms and infrastructures to others, such as

Amazon, Oracle, Microsoft, Google, and IBM. Amazon has focused on providing web

services that allows companies to easily deploy their web-based applications and only

pay for the amount of computing they use (Amazon, 2018). Similarly, Oracle provides

infrastructure as a service, that does away with requiring companies to make expensive

upfront capital investments in Oracle hardware and simply pay a subscription for the

computing services they consume (Oracle, 2018). Table 1 illustrates how quickly the

cloud computing business has grown and how it will continue to grow through 2021/2022

as described by its compound annual growth rate (CAGR).

Table 1: Forecasted Growth of Cloud Computing

Cloud Computing Description	Forecasted Value	CAGR	Source
Worldwide Public Cloud Services	2021 - $277 billion	21.9%	(IDC, 2018b)
Worldwide Private Cloud Services	2021 - $99 billion	45.71%	(Statista, 2017)
Off-Premises Public cloud Enabling IT infrastructure	2021 - $42.6 billion	12.1%	(IDC, 2018a)
Off-Premises Private cloud Enabling IT infrastructure	2021 - $9.2 billion	11.7%	(IDC, 2018a)
Worldwide Enterprise Storage for Cloud Market	2022 - $88.8 billion	23.7%	(MarketsandMarkets, 2018)

Upon taking leadership of Microsoft as the new CEO in 2014, Satya Nadella, stressed the

importance of mobility and clouds upon his employees, on his first day on the job,

declaring it was their job that "Microsoft thrives in a mobile and cloud-first world

(Nadella, 2014)." Over the past few years, IBM has been making key acquisitions in

various cloud-based companies (Barker, 2014) (IBM, 2013) (IBM, 2014) and has

integrated their existing tools and services with the acquisitions in order to develop cloud-based services and products to compete against similar products offered by companies such as Amazon and Oracle (Dignan, 2014).

Even Google's head of technical infrastructure team, Urs Hölzle, has changed the team's priority from servicing internal company products such as Gmail and Google Maps and focusing the team's resources on the expansion of Google cloud services (Metz, 2014). Similar to Microsoft, Oracle, IBM, Google is also offering cloud-based enterprise tools that rivals Amazon's that allows companies to host and develop their software on Google's architecture (Google, 2018). Amazon was one of the initial pioneers in offering cloud computing services to companies, and thus, has a healthy lead in market share compared to its closest competitors (Relan, 2014). Figure 1 shows how far ahead Amazon took advantage of their head start with its cloud-based products, and has more market share than three of its closest competitors (Smith, Liu, De Leon, Ball, & Stahnke, 2018). The remaining 42% of the market is scattered amongst smaller company offerings (Smith et al., 2018).
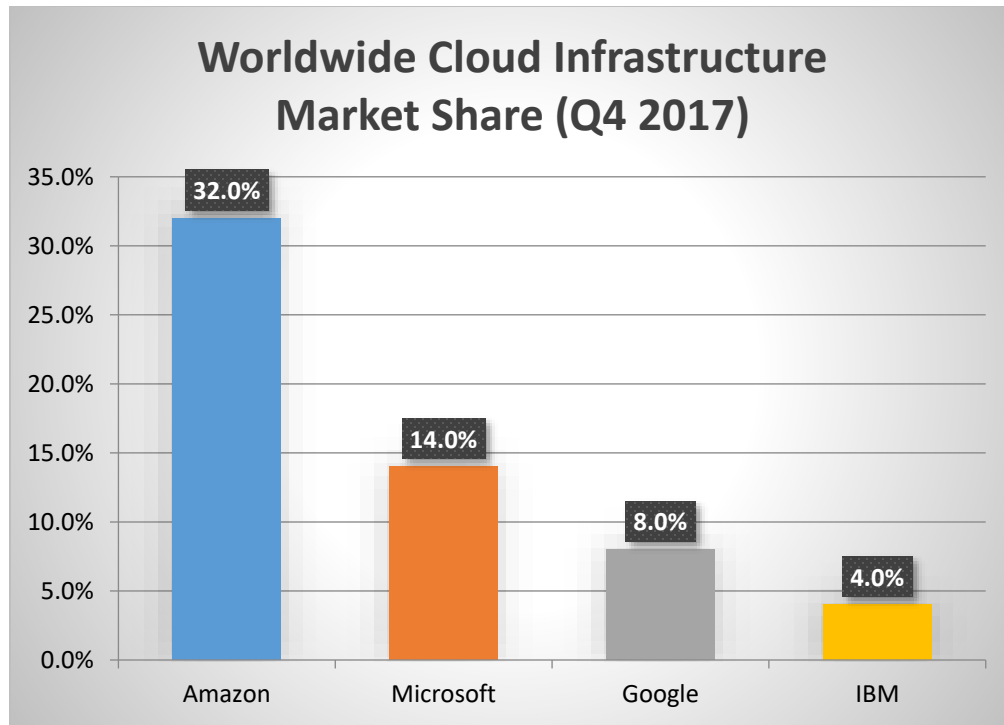
Figure 1: Worldwide Cloud Infrastructure Market Share Q4 2017 (Smith et al., 2018)

By having cloud-based computing available to companies and individuals, it further strengthens the idea that anyone can possess a computing device powerful enough to run sophisticated applications from anywhere, given a strong enough network connection. Why not take advantage of the clouds for the advancement of intelligent tutoring systems?

<div align="center">Intelligent Agents</div>

Before delving into intelligent tutoring systems, it is important to understand what intelligent agents are and how they operate. An intelligent agent first builds upon a traditional agent where the universally agreed upon definition for an traditional agent is an autonomous entity that will sense the environment where the agent may choose an

action for which it may perform in order to meet the agent's goals (Wooldridge, 2000).

The reason why the definition for an agent cannot be expanded upon further is that due to

varying domains, the composition of an agent will change (Wooldridge, 2000).

Wooldridge provided one example of varying agent composition as it deals with learning

since some domains will require the agent to learn as it interacts with the environment,

while other domains do not require the learning to take place (Wooldridge, 2000).

An intelligent agent goes further by requiring the agent to possess three additional

qualities: timely reactivity to the environment, proactive actions by taking the initiative to

meet its goals, and the capability to interact with other agents (Wooldridge, 2000). The

difficulty in designing intelligent agents is that there must be a fine balance between

performing actions which are simply reacting to the state of the environment and actions

which allow the agent to better its chances at achieving its goal (Wooldridge, 2000).

When discussing the social component of an intelligent agent, the interaction between

agents isn't simply an exchange of information, but a negotiation where the final actions

are to the betterment of both agents and not a one-sided transaction (Wooldridge, 2000).

Multi-agent systems incorporates agents (including intelligent agents) in order to develop

a system that meets the intent of the system (Huhns & Stephens, 2000). These agents

would be responsible for different aspects of the system and allows system developers to

apply the divide-and-conquer approach by focusing on individual autonomous agents

(Huhns & Stephens, 2000). The idea of multi-agent systems have generated proposals of

E-Learning architectures on a single system (Sakthiyavathi & Palanivel, 2009) and later

have been updated to incorporating cloud-based theories (Babu, Kulkarni, & Sekaran,

2014). The evolution of the E-Learning architecture to cloud-based technologies allows

for the system to benefit from cloud-specific features (Babu et al., 2014) such as

scalability, simplicity, and affordable pricing (Grossman, 2009).

<div align="center">Intelligent Tutoring Systems</div>

A classification of training systems, called Intelligent Tutoring Systems (ITS), can be

composed of intelligent agents, such as an intelligent tutor (Giraffa & Viccari, 1998).

Like intelligent agents, intelligent tutors have a set of teaching objectives and will react to

student responses in order to meet those goals (Giraffa & Viccari, 1998). Since there can

be numerous specialized agents within an intelligent tutoring system, these agents must

communicate with each other. Through the coordination between these agents,

intelligent tutoring systems provide the user some type of learning without requiring the

need for an instructor (Corbett, Koedinger, & Anderson, 1997).

From a historical perspective, computers have been used to teach mundane tasks starting

from the 1960s, but it wasn't until the early 1970s that the idea of having some

intelligence behind the tutoring system would be formulated. (Corbett et al., 1997). Since

the 1970s, there has been an enormous amount of academic contributions to Intelligent

Tutoring System research, but its architecture can be seen as possessing four distinct

sections: domain model, student model, tutoring model, and the user-interface model

(Sottilare, Graesser, Hu, & Holden, 2013, p. ii). The domain model encompasses the

specific data that the ITS will teach to the student (Sottilare et al., 2013, p. ii).

Likewise, the student model represent all aspects of what the student knows and how they feel with respect to the teaching (Sottilare et al., 2013, p. ii). Using both the student and domain model, the tutoring model will use internal algorithms in order to determine how to improve learning efficiency (Sottilare et al., 2013, p. ii). Between all these components and the user, sits the user interface model which receives input and displays output. This piece of ITS functionality will monitor any sensory readings from the student and will provide feedback to the student that was generated by the tutoring model (Sottilare et al., 2013, p. ii).
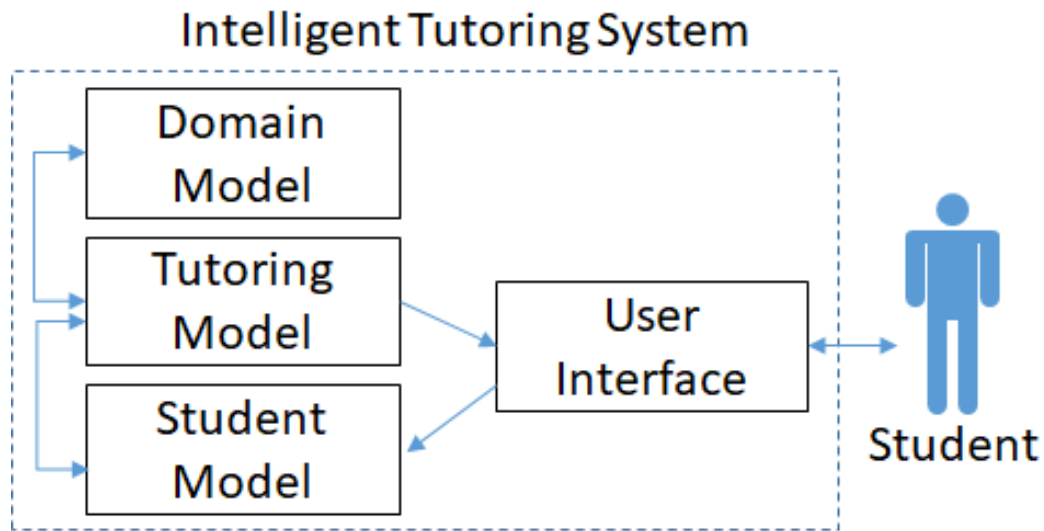
Figure 2: ITS Architecture (Sottilare et al., 2013)

The purpose of the sensor data collection is to identify the state of the learner. The state of the learner is an important input to the ITS's decision process and adaptability to the new learner state (Sottilare et al., 2013, p. ii). For example, students learning physics may use a physics tutor to solve problems which would obtain student facial marker sensor data to identify a confused learner state. This confused learner state may force the

ITS to utilize a reflective prompt that walks the student through the process of solving the problem. Student tracking isn't new, as it has been utilized in a multitude of different learning management systems such as BlackBoard, WebCT, and TopClass (Romero, Ventura, & García, 2008). With the data being collected, the ITS can better decide how to support the user with context-specific help or decide to move on to the next learning objective. However, the reliability of sensors and accuracy of the classification algorithms are critical to the tutor being able to select optimal strategies tailored for that individual learner.

Another benefit of having statistics is that the administrators or instructors can review the data in a report or graph to better analyze overall progress. Depending on trends, the instructors can provide an extra layer of support and guidance to further improve any deficiencies. Furthermore, by employing a web-based ITS, these reports can be accessed from anywhere, from a cloud-based web-service, or served up directly from the system on-the-fly. The administrators do not need to be tied into a specific computer at a specific location but can leverage the internet for more flexibility.

Many will believe that the motivation moving Intelligent Tutoring Systems research along is to move toward the success which one-to-one tutoring can have on a student's learning. For example, in 1984, Bloom showed that one-to-one tutoring by a human will allow a student to be two standard deviations better than an average student learning via conventional methods (Bloom, 1984). A system– in virtual tutor - that would produce such results or even greater would reduce the strain of requiring a dedicated tutor for each student, allowing the tutor to be more efficient and manage multiple students at once.

An intelligent tutoring system may not be equivalent to a virtual tutor. It isn't sufficient to produce an ITS without taking the intended audience and his/her interaction and level of affect for the ITS into consideration. There have been studies that have shown there are different audiences which may be more inclined to prefer one type of learning system versus others based upon different variables (Proctor, Lucario, & Wiley, 2008) (Proctor & Marks, 2013). An example of an audience using age as a variable, Proctor and Marks have shown evidence that there are two different learning communities of school children, kindergarten through fifth grade, and sixth grade through twelfth grade (Proctor & Marks, 2013).

Another example of audiences related to another variable such as college education, as explained by Proctor in the analysis of college-educated junior officers' reluctance to accept serious-game training versus regular enlisted personnel (Proctor et al., 2008). Customer affect is not missed by the computer and mobile device industry (Rodriguez, 2014) (Swayne, 2014). Steve Jobs is well known for taking the reins of Apple and steering them in the right direction in the 1990's (LaMonica, 2011). In the 2000's, Jobs was well known for iPods, iPhones, and iPads that consumers "loved" (Zachary, 2011). Competitors strive to capture a similar level of affect among their consumers as exhibited by "Life Companion" caption displayed on the log on screen for the Samsung Android smartphone (Gasior, 2013). Therefore, it is imperative that the intelligent tutoring system account for affect in the audience during its design phase in order to increase its efficacy (Rodrigo et al., 2008).

In the same way students have varying levels of experience and expertise, tutors will also

differ in effectiveness. Another motivation for ITS advancement stems from the fact that

studies have shown that tutors must also be trained in order to achieve their full potential

("Evidence That Tutoring Works," 2001). Training includes interpersonal skills to

reduce impatience with students and in strategies to lead the students towards their

learning goal ("Evidence That Tutoring Works," 2001). In order to achieve the benefits

that Bloom has shown, we would require tutors that are highly trained. Thus, if

successful intelligent tutoring systems can be developed, which would operate at the

efficiency of a well-trained tutor, the students would stand to reap the most benefit. To

be successful, the system does not necessarily need to be a comprehensive solution but

may be assigned the task of tutoring students the mundane foundation-type material, and

let the more experienced human tutors to focus on the advanced material (VanLEHN,

2011).

The goal of substituting a tutor with a sophisticated system, to increase tutoring

efficiency, isn't the only motivation for the advancement of ITS technology. Another

motivation is the accessibility of intelligent tutoring systems within formal educational

environments, such as online courses. In the past, traditional collegiate online courses

consisted of Microsoft PowerPoint slides, online quizzes/tests, participation in message

boards, recorded video, and assignments. Now, there are instances where intelligent

tutoring systems are integrated within the curriculum for the online course, such as the

Bayesian intelligent tutoring system, or BITS (Butz, Hua, & Maguire, 2004) for short.

BITS provides the student gentle feedback and tries to determine when the student is

having issues when suggesting learning objectives (Butz et al., 2004).

Another example of a tutoring system is the system from textbook publisher McGraw-

Hill named LearnSmart, which is integrated with their Connect environment (McGraw-

Hill, 2013). Similar to BITS, LearnSmart will also provide feedback with respect to the

student's progress, and LearnSmart will also adapt its teaching material depending on the

student's mastery of the material (McGraw-Hill, 2011). Furthermore, one of the

highlights of the LearnSmart system is how it caters to today's student through its

accessibility and engagement (McGraw-Hill, 2011). Today's college student isn't

content to study via one specific computing device, but would like to be able to access

the class material such as their textbook, notes, and/or class slides from anywhere (Pierce,

2013). The students currently enrolling in college are accustomed to being able to access

digital information whenever and wherever they see fit (Pierce, 2013) (Protalinski, 2011).

Thus, the LearnSmart system not only provides access from traditional desktop and

laptop computers, but also allows access to the study material from tablets and mobile

phones. The aspect of accessibility is important since this feature showcases the fact that

people nowadays will possess a multitude of internet-connected devices, allowing them

to learn anywhere and at any time.

<div align="center">User Interface</div>

This study will focus on the use of multiple sensors in an intelligent tutoring system,

which reside in the user interface section of the system architecture, visually depicted in

Figure 2. A wide variety of research shows how various studies and implementations integrate various sensor technology and highlight their usefulness. In addition to the use of sensor data, there is also research that tries to interpret the learner's affect state using keystrokes and mouse movements (Zimmermann, Guttormsen, Danuser, & Gomez, 2003), although how this would translate to tablet touch gestures remains a work in progress.

One prime example of how sensory data can be used in an ITS is the work done by Sottilare and Proctor (Sottilare & Proctor, 2012), where the intelligent tutoring system attempts to interpret and predict the mood of the students in order to tailor the tutor specifically to that student at that given time. Or when D'Mello et. al conducts a study where they gather sensory data while students interact with the AutoTutor software by tracking eye position, body posture and video recording (D'Mello, Graesser, & Picard, 2007).

Intelligent tutoring systems have evolved into equipping one or more types of sensor which allows the system to detect the emotion and state the user is experiencing, shown in Figure 3. There can be many types of sensors used with these systems such as: postures analysis seat, conductance bracelet, facial expression sensors, pressure mouse, blood pressure monitoring, and so forth (Frasson & Chalfoun, 2010).
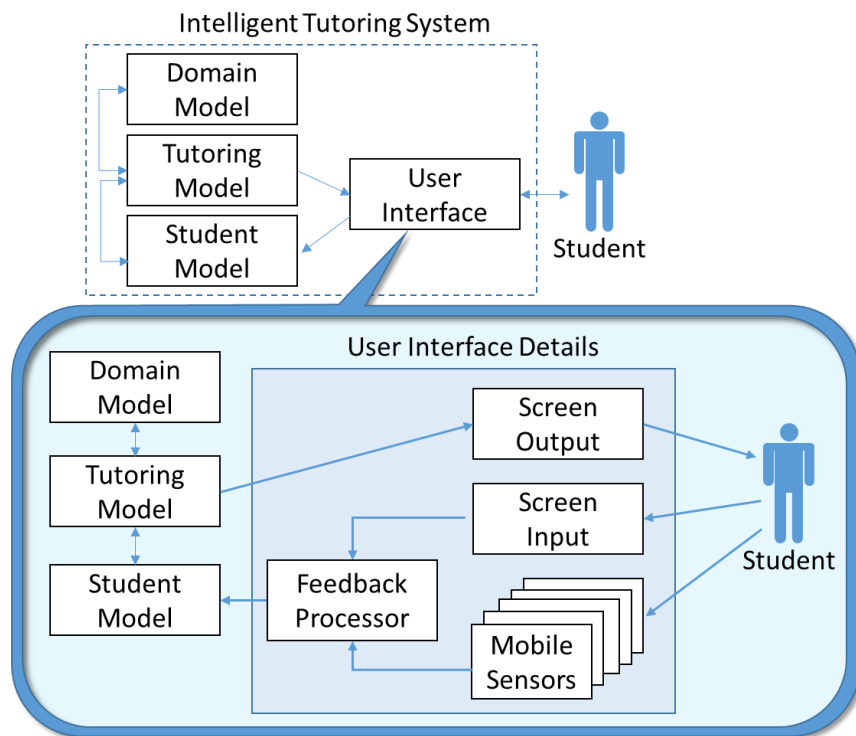
Figure 3: Detailed User Interface ITS Architecture

Table 2 presents a quick discussion on how a traditional desktop sensor can be used in a mobile environment.

Table 2: Sensor Table

Sensor Type	Mobility?
Camera	Studies by D'Mello et. al (2007) uses a camera that is mounted in a fixed position. Camera can be mobile if mounted as such.
Posture Sensor (seat sensor)	Research done by Woolf et. al (2007) uses a posture sensor which can detect the posture of the subject. The sensor must be installed onto a chair which makes mobility an issue.
Bluetooth Skin Conductance Sensor	In the study performed by Woolf et. al (2007) shows the level of "arousal". By using Bluetooth, this sensor is mobile.
Pressure Mouse	Utilized by Arroyo et. al (2009), will detect the pressure the student will impose upon the mouse, detecting varying levels of frustration. Since the mouse requires a tracking surface, and although it may be wireless, lends to be a non-mobile sensor.
Pressure Keyboard	Utilized by Graesser (2005), the pressure keyboard detects the force the student has on the keyboard, helping to detect emotional state. Similar to the pressure mouse, the pressure keyboard could be wireless, but the keyboard must be resting on a surface, therefore, the keyboard leans toward stationary.

The key takeaway here is that there have been contributions on how sensory information is obtained, processed, and utilized within the intelligent tutoring system in order to make the learning more effective. However, these examples primarily revolve around systems in a traditional computer environment.

CHAPTER TWO: APPROACHES

If one is to research the efficacy of a sensor driven intelligent tutoring in a mobile

computing system to improve personalization, a technology approach to implement the

ITS with sensors must be considered as well as a research approach for gathering user

outcomes that relate learning efficacy.

Technology

Technologically, as previously discussed, there has been a growth in use and acceptance

of the mobile computing platform, more noticeably, in tablets. We have also discussed a

few examples how mobile technology was used for learning. However, I would like to

review existing mobile-related ITS concepts and systems which have been discussed in

academia. I will start off by reviewing tablet PCs using traditional interfaces that utilize

windows, icons, menus and pointers (WIMP) (Baecker, 2008), and then provide an

overview of mobile application user interface design.   Subsequently, I will review the

use of sensor technology within mobile applications and various reporting and

monitoring methodologies used.

Tablet PCs and WIMP

The use of the stylus or pen instruments to interface with a tablet computer is a pointer

like a mouse though it is considerably different from fingers. Finger interfaces will be

discussed after this section. Mouse, stylus, and pen pointers are a categorization within

human computer interaction commonly known as WIMP, which is short for: windows,

icons, menus, and pointers. When the computing platform from a desktop is transformed

into a tablet, the mouse is no longer practical and is replaced with the stylus. Although

modern tablets feature the capability to use finger control, a stylus is used when high

accuracy navigation is required (Pogue, 2012), because the stylus allows the tablet to

retain the same WIMP software design principles prevalent on a desktop computer.

For example, some tablets such as those developed by Getac or Panasonic running

WIMP-based operating systems (e.g. Windows 7), absolutely require an accurate pointer.

Thus, stylus and pen-based user interfaces still remain popular due to the finer control

they provide (Pogue, 2012). The area where pen-based interfaces truly shine is when the

user is allowed to freewrite directly into the application, such as handwritten text

(Anthony, Yang, & Koedinger, 2012). However, handwriting recognition is still a work

in progress and systems must take account of this when designing a system (Anthony et

al., 2012). Therefore, it is important to determine the best application in which this type

of interface is used, such as in Anthony et al's algebra equation solving ITS. In Anthony

et al's handwriting ITS implementation, it is shown that the learner finds entering

equations into the system to be more intuitive than by traditional means (Anthony et al.,

2012).

Another pen-based ITS is one named Newtons Pen, which was developed for an

undergraduate statics course (C. Lee, Jordan, Stahovich, & Herold, 2012). Newtons Pen

utilizes commercial off-the-shelf (COTS) hardware, LeapFrog's FLY Pentop Computer,

as the interface to their ITS. The FLY Pentop is a wide pen that will recognize what is

being drawn on special paper and this information is processed and communicated back

to a computer (McHugh, 2005). In Lee et al's study, they combined the pen with a tablet

PC, although the documentation didn't mention specifics on the computing hardware

used. This pen allows the user to draw diagrams and highlight the concepts which are

important in the statics course, such as "free body diagrams and deriving equations"

The common trend in these two pen-based systems is they are trying to break the mold

imposed by WIMP-based design methodologies. Lee et al achieved their goal of

receiving 'favorable' response to the system from its students. Anthony et. al achieved

data entry of algebraic equations into the system at a rate which was twice as fast

compared to traditional keyboard/mouse entry (Anthony et al., 2012). There is a benefit

of breaking from a WIMP interface design, if the intended use case can justify it.

Finger-Based GUI Design

When Steve Jobs introduced the original iPhone at MacWorld 2007, he amazed the

crowd with finger-based navigational gestures such as touchscreen "pinch-to-zoom,"

"one-finger scrolling," and "sliding" to interact with on-screen elements without the need

for pointing and clicking with a stylus (Honan, 2007). The audience members simply

were not familiar with the long history of multi-touch technology and were presented

with what appeared to be new technology in a well-designed package. Bill Buxton

(2008) defines the concept of the "Long Nose of Innovation" where the latest gadget,

which utilizes the 'big idea,' has been around for a considerable amount of time before it

becomes popular.

Before the sale of iPhones in 2007, finger-based (or hand-based) touchscreen

navigational gestures could have seen its origins in projects from the late 1970s through

the early 2000s, such as VIDEOPLACE in 1983, Fingerworks in 1998, and Diamond

Touch in 2001 (Buxton, 2013). However, since these works were not highly popularized

outside the Human Computer Interaction community, credit for the research tends to be

directed solely at the Apple Corporation with the iPhone. Furthermore, although not tied

to touchscreens, touchpads, invented by George Gerpheide (5305017, 1994) have been

incorporated into laptops and other computing devices which have played an important

role with finger-based navigation (Ryan, 1999).

Since the release of the original version of the iPhone, companies such as Samsung,

HTC, and Motorola have released phones and tablets that feature touchscreens that

feature similar functionality. Moreover, there have been numerous patent trials where

Apple has sued other companies for the attempted infringement of their patents with

mixed results (Patel, 2012). Three examples of technologies which have been accused of

infringement include: performing an action from a computer structure (5946647, 1996),

universal interface for retrieval of data (6847959, 2000), and unlocking device with slide

gestures (US8046721, 2009).

Marketplace competition aside, the astronomical rate of tablet adoption can be attributed

to its easy to use touch screen interface design, especially via a finger (D. Lee, 2011).

Thus, finger-friendly operating systems would need to be developed, such as Windows 8,

iOS, Android, etc. For this reason, Microsoft elected to design Windows 8 to support a

user interface that did not require an accurate pointer, i.e. mouse or stylus, but allowed

for the comfortable navigation via fingers (Microsoft, 2014).

<center>Mobile App UI Design</center>

An important aspect to consider is the user interface design when the tablet platform is

targeted, especially when we are moving away from a WIMP-based paradigm. When

designing applications for a platform, such as iOS, Android, and so forth, there are

avenues the developer may take: developing the application as a web-based application or

implementing the application as a native app (Stark, 2010).

Web-based applications can be designed and developed with common web-based

standards, such as HTML 5.0, CSS, and JavaScript (Gavalas & Economou, 2011). The

idea behind a web-based application is that as long as the device has the appropriate web-

browser that supports all these technologies, the user will be able to immediately interact

with the service via the browser (Stark, 2010). This will allow developers to learn and

master only one set of technologies and develop across many platforms (Wasserman,

2010). Furthermore, software updates, such as bug fixes and newly developed

functionality, can be deployed instantly without any required user action (Stark, 2010).

The other method of developing mobile applications is to develop them specifically for

the native platform. These mobile applications follow the recommended look-and-feel of

that specific operating system and can better interact with the resources on the device

(Heitkötter, Hanschke, & Majchrzak, 2013). Native apps need to be written using

specific development environments including different language requirements and have specific (or recommended) guidelines that developers must follow. Depending on the operating system, publishing the application to an audience may require to get certification or an approval in order to be included on that platform's store (Stark, 2010).

Therefore, unlike web-based applications, it takes a considerable amount of effort to learn the intricacies of development, and developing a native app across multiple platforms which requires an extensive amount of rework (Wasserman, 2010). Large companies will maintain separate product teams that maintain a specific version tied to a specific platform, and each team will push out updates and functionality at different product cycles (Wasserman, 2010).

When native apps are compared to their web-based counterparts, it may seem difficult to justify the extra expense and overhead, but there are inherent advantages in choosing native apps. Since native apps are developed specifically for a platform, designers can lay out a user interface that is functional and aesthetically comfortable to use (Heitkötter et al., 2013). These apps will match the 'look-and-feel' of other apps on the device and thus, will allow for a cohesive user experience (Heitkötter et al., 2013). Furthermore, since native apps are directly communicating with the operating system, the app can take advantage of platform-specific functionality such as creating shortcuts, use of the notification center, providing customized widgets, and so forth (Heitkötter et al., 2013).

Moreover, native apps can directly access hardware resources that are currently available on the device as soon as the device is released (Mahemoff, 2011). Web-based

applications are at the mercy of the standardization of Application Programming

Interfaces (API) that allow for the web-based application to interact with the hardware

resources via HTML5. The organization responsible for setting the standards is the

World Wide Web Consortium (W3C), although the standardization process is extremely

slow (Shankland, 2011). For a standard to be recommended for implementation, it must

go through four different stages: Working Draft, Candidate Recommendation, Proposed

Recommendation, and W3C Recommendation ("World Wide Web Consortium Process

Document," 2005). With so many stages and testing, if the latest technology is to be

used, developers may be forced to use native apps versus web-based apps (Mahemoff,

2011).

However, there is plenty of effort being spent in order to increase the performance of

web-based technology, such as JavaScript, by the big players in internet computing, e.g.

Microsoft, Google, Apple, Opera and Mozilla (Charland & Leroux, 2011). It can be said

that a few years later that the performance between native apps versus web-based apps

would be the same, but for now, native apps tend to be quicker (Charland & Leroux,

2011), sport better user interfaces (Charland & Leroux, 2011), and employ hardware

resources (Charland & Leroux, 2011). For example, the US Army has been performing

trials where soldiers have been equipped with customized mobile devices (smartphones

and tablets) which run a mixture of platform-independent web mobile applications and

platform-specific native applications (Protalinski, 2011).

With respect to examples of current implementation of ITS, any web-based

implementation will function on mobile devices, since latest generation devices have

sophisticated web browsers. However, due to the small form-factor of these devices, if the ITS is not optimized for the screen, the user will be forced to pinch and zoom in order to navigate through the interface. This will impose an extra barrier in terms of ease of learning upon the user. Furthermore, by integrating the ITS with a native mobile application, the application can get direct access to any attached hardware easier than a web application (Charland & Leroux, 2011).

Conversely, one example of an ITS being designed explicitly for a mobile device is the ITS that teaches users how to play Sudoku. This system runs on an Android smartphone, and interfaces with a database via a web server (Zhuang & Cheung, 2013). The reason why the authors decided to go with a native app development effort was due to the fact that this system requires a clean and exact user interface. It wouldn't be possible to get the exact layout rendered correctly if HTML5 was used (Zhuang & Cheung, 2013).

<div align="center">Sensors in Mobile Applications</div>

The proliferation of mobile devices has forced hardware manufacturers to add features and capabilities in attempts to differentiate themselves from the others (ATKearney, 2013). Once a device manufacture introduces a feature, other manufacturers quickly implement similar feature sets (Ekekwe, 2012) until it becomes standard in all devices such as front-facing cameras, near field communication (NFC), infrared blasters, and front-facing speakers. These new hardware capabilities allow for the development of software which takes advantage of data and environment which wasn't previously possible. For example, mobile applications that utilize NFC capabilities can now

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automate actions based upon what the NFC chip instructs the phone to do, such as change

phone settings, report into social media websites, or download a business' contact

information (McFerran, 2012).

Moreover, with the spread of mobile devices, comes the opportunity to incorporate

accessories which could monitor the student without becoming a major distraction to the

student. With devices running Android 4.3, iOS 5, or Windows 8, there is support for

Bluetooth SMART (or LE for Low Energy) which allows for communication to a variety

of different pulse and heart rate monitors that do not consume battery power excessively

(Casserly, 2014). There also exist phones which will detect user fingers which are almost

touching the screen, commonly referred to as a finger hover, which can add another

dimension to user interactivity (Moghaddam, 2014). Coupled with decent front facing

cameras built into the devices, proposed intelligent tutoring systems can monitor the heart

rate, eye retinas, and facial expressions of the student and incorporate this data to better

tailor their learning strategy.

The Sudoku ITS, which utilizes an Android device, does not explicitly take advantage of

any sensor technologies (Zhuang & Cheung, 2013). Instead, the only direct mechanism

for which the application can get actual metrics on the student is to determine how long it

has been between user actions (Zhuang & Cheung, 2013). In addition to this time metric,

the application keeps track of the current difficulty of the puzzle and a "user profile",

which is simply a history of how many games the student has played. Once the time

since last action has grown too large, hints are automatically displayed for the user

(Zhuang & Cheung, 2013). The Sudoku ITS could have taken advantage of the sensor technology available and incorporated them into the study.

<div align="center">Student Affect and Engagement</div>

However, even with the incorporation of the latest technology being applied to tutoring systems, the emotional state of the student is an aspect of learning that shouldn't be ignored (Woolf et al., 2009). At a fundamental level, human instructors are able to pick up on emotional cues of their student, and will adapt their teaching strategies accordingly (Porayska-Pomsta, Mavrikis, & Pain, 2008). Thus, it's not surprising that studies have shown that there is a strong relationship between affect and learning (Woolf et al., 2009).

When Forbes-Riley and Rotaru conducted their student affect study on a spoken dialog tutoring system, they proposed the idea that when there was an absence of affect, the student did not experience any learning and were disengaged (Forbes-Riley, Rotaru, & Litman, 2008). A popular definition for computer engagement was provided by Laurel where she referred to engagement as, "a desirable, even essential, human response to computer-mediated activities" (Laurel, 1993). An interesting breakdown of engagement was presented by O'Brien and Toms which broke down engagement into a series of attributes: attention, novelty, interest, control, feedback and challenge just to name a few (O'Brien & Toms, 2008).

The use of affect to improve ITS learning effectiveness has already been approached by numerous researchers, such as D'Mello's study where they integrated the use of affect-specific sensors into AutoTutor (D'Mello et al., 2007) (D'Mello, Olney, Williams, &

Hays, 2012). The conclusion of these studies indicate that the use of sensors to detect

student's affect state could improve the effectiveness for the tutoring (D'Mello et al.,

2012). Therefore, student affect and their engagement must be taken into account in

order to design a successful tutoring system (Picard et al., 2004).

<center>Research Approach</center>

As indicated above there is currently a lack of research on tailored use of sensors

available on a mobile tablet for use in intelligent tutoring systems designed to run

specifically on a tablet. Existing web-based and native applications on tablets are simply

tutors that rely on textual input and are aimed at a specific audience, teaching a specific

topic, such as the development of "ExploreIT!" (Blessing, Skowronek, & Quintana,

2013) or "Math Tutor" (Masood & Hoda, 2014). Although these applications have

limited success within their intended scope, they do not have the capability to monitor the

progress of the student nor dynamically change their tutoring strategies. The only ITS

that runs on a mobile device, Sudoku ITS, simply does not go far enough by not

incorporating sensor technology. Sensor technology would allow the system to respond

dynamically to the user without simply keeping track of time and a user profile.

The opportunity exists to take advantage of actual sensors and incorporate them into a

mobile tablet. The potential of sensors, available on tablets such as Bluetooth heart rate

monitors and the on-board camera to detect face and eye gazes, to enhance tablet-based

intelligent tutoring systems is not currently discussed in the literature.

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In order to advance understanding the potential of sensors to enhance tablet-based intelligent tutoring systems, a native Android app is required to be designed and implemented. Since the application will be native, it will have access to onboard hardware such as the camera and be able to access paired Bluetooth devices via Android calls. This Android app would then have to communicate with an Intelligent Tutoring System via its wireless connection which will serve up the relevant content. This content would need to be authored and a study to be performed targeting an introductory college level course. In order to realize this study, the Generalized Intelligent Framework for Tutoring (GIFT) framework, an existing open source intelligent tutoring framework system (Sottilare, 2012), would be employed to facilitate the use of an existing ITS that allows modifications in order to communicate with the newly developed Android application.

CHAPTER THREE: RESEARCH METHODS

Introduction

Mobility introduces new opportunities and challenges particularly in terms of utilizing sensors to enhance the mobile tutoring experience for the student.   This research proposes to explore the potential opportunities and challenges of an ITS on a mobile-computing platform. Exploration topics include methodology for user input, design of the graphical user interfaces, effectiveness of sensor types, and potential design of intelligent tutors which makes use of cloud computing and mobile sensors. This research will quantify the performance of students using an Android application on a tablet, based upon a prototype, which interfaces with the Generalized Intelligent Framework for Tutoring (GIFT). We wish to explore the impact of using mobile sensors on tablet-based intelligent tutoring systems in various settings and measuring their engagement to improve personalized learning.

Resources limit the exploration of the experimental hypotheses discussed below to a single successfully-tested mobile ITS prototype system. The mobile ITS prototype may be generalized in that it is an android tablet with a GIFT-based tutor interface integrated with a Bluetooth heart rate monitor and camera. The heart rate monitor on the fore mentioned mobile prototype may be replaced prior to conduct of the formal experiment with a Q sensor, Empatica E4, or Microsoft Band 2 depending on reliability, availability, and capability to be integrated into the existing mobile prototype. The strength of assumed equivalence of interest and skills among subjects constrains exercise

content. Given the planned general population, the experiment proposes use of a simple

puzzle game described at

https://play.google.com/store/apps/details?id=com.uberspot.a2048. Past literature

indicates controversy about whether a test vehicle should focus on numbers, historically

biased by interest and/or skills toward males, or words, historically biased by interest

and/or skills toward females. Due to resource limitations, this research chose to accept

potential bias to engagement due to interest or skill differences and proceeds with a

numbers puzzle as the test vehicle. None the less, the research experiment may be

performed in future research on various audiences whether it be with a word game or one

of any number of academic or subject matter topics. Test limitations will be noted in

concluding analysis and/or publications. This puzzle engages subjects to combine

numbers to make a larger number rewarding larger numbers more than smaller numbers.

Initial testing of the games indicates that subjects are expected to be engaged

conceptually with that engagement manifest in gesture frequency. If constrained by time

and rewarded by scores, engagement is expected throughout a short game period.

Another advantage of this particular game is that the source code is available and

should be "fairly" trivial to insert into the prototype intelligent tutoring app and keep all

the existing prototype Bluetooth Heartrate and camera data intact. Since the subjects are

volunteers, the research focuses primarily on data collection protocols with game

performance as a side product. Performance improvement between practice session and

gaming session will be measured in terms of score.

When using a tablet or a mobile device, there are a few main postures a user can exhibit: sitting at a desk or table, lounging on a recliner or sofa, standing, and supine or lying flat on a bed. Out of these four positions, the occasion of running into the supine position is less common than the other three. Therefore, this study will focus on the three more common ergonomic positions, sitting, lounging, and standing.

Research Questions and Hypotheses

Given a game on a mobile ITS prototype system (e.g. tablet) as an interim substitute for an ITS, this research will attempt to answer the following research questions:

1. Does the quality of the tablet's camera provide an effective mechanism to track eye gaze for a given ergonomic position? (Descriptive statistics to be collected in each ergonomic position)

2. Does the quality of the tablet's camera provide an effective mechanism to track facial expression for a given ergonomic position? (Descriptive statistics to be collected in each ergonomic position)

3. Does the ergonomic position of the user impact the effectiveness of the tablet camera's face detection?

   $H3_0$: The tablet camera's face detection capability is equally effective in all selected ergonomic position.

   $H3_A$: The tablet camera's face detection capability is NOT equally effective in all selected ergonomic position.

4. Is face detection (or camera gaze) rate correlated with touch gesture frequency rate by different ergonomic positions?

> $H4_0$: The tablet camera's face detection rate and touch gesture frequency rate are equivalent for each ergonomic position.

> $H4_A$: The tablet camera's face detection rate and touch gesture frequency rate are NOT equivalent for each ergonomic position.

5. Does the wrist monitor provide an effective mechanism to track heart rate activity when paired with a tablet? (Descriptive statistics to be collected in each ergonomic position)

6. Does the wrist monitor provide an effective mechanism to track electrodermal activity when paired with a tablet? (Descriptive statistics to be collected in each ergonomic position)

7. Does the wrist monitor provide an effective mechanism to track skin temperature when paired with a tablet? (Descriptive statistics to be collected in each ergonomic position)

8. Does the user's ergonomic position impact the electrodermal activity captured by the wristband?

> $H8_0$: The electrodermal activity captured by the wristband is equivalent for each ergonomic position.

> $H8_A$: The electrodermal activity captured by the wristband is NOT equivalent for each ergonomic position.

9. Is the electrodermal activity captured by the wristband correlated with touch gesture frequency rate by different ergonomic positions?

> $H9_0$: The electrodermal activity captured by the wristband is correlated with touch gesture frequency rate for each ergonomic position.

> $H9_A$: The electrodermal activity captured by the wristband is NOT correlated with touch gesture frequency rate for each ergonomic position.

10. What is the relationship between the game score performance and the ergonomic position of the user?

> $H10_0$: The game score performance by ergonomic position of the user is equivalent.

> $H10_A$: The game score performance by ergonomic position of the user is NOT equivalent.

11. What is the relationship between the delay between game moves and the ergonomic position of the user?

> $H11_0$: The delay between game moves and the ergonomic position of the user is equivalent.

> $H11_A$: The delay between game moves and the ergonomic position of the user is NOT equivalent.

12. Can a pressure sensitive stylus be used in conjunction with the ITS in order to determine the level of student engagement?

Although a stylus that is equipped with a pressure sensitive sensor offers interesting research opportunities, manufacturers have not developed enough options for the Android platform. Therefore, this research question is beyond the scope and not considered in this dissertation research.

13. Can a pressure sensitive touch screen be used in conjunction with the ITS in order to determine the level of student engagement?

In order to fully explore this question, a pressure sensitive screen is required. Unfortunately, there isn't a wide availability of Android pressure-sensitive tablets in the marketplace. Thus, this research question is beyond the scope and not considered in this dissertation research.

<u>Research Design</u>

The study will employ a hybrid of user-reported and system observed approaches to data gathering and hypothesis testing for each indoor physical setting as shown in Table 3: Sequence of Activities, Data Collected, and Data Collection Protocols, which also includes the recording rate (if applicable).

Table 3: Sequence of Activities, Data Collected, and Data Collection Protocols

Activity Sequence / Data Collection Protocol (Rate)	Pre-Session Data Collection	Practice Session	Play Session	Post Session Data Collection
Demographic Questionnaire	X			
Skin Temperature (1 Hz)	X	X	X	X
Puzzle Game Scores		X	X	
Heart Rate (1 Hz)	Monitor Attached	X	X	Monitor Detached
Eye Gazes (1 Hz)		X	X	
EDA (5 Hz)	Monitor Attached	X	X	Monitor Detached
Gesture Data (On-demand)		X	X	
Time Elapsed		X	X	
Affective Slider	X			X
User Satisfaction Survey				X
External Camera Recording Study	X	X	X	X

System observed data will be obtained from sensors monitoring users while they interact with the mobile application, whereas self-reported data is gathered via user surveys and feedback. Together, the data will be used to answer the research questions and hypotheses proposed by the study. The study uses an experimental design where the participants will self-select one of three settings that will affect their posture. Subject numbers will be such that setting treatment will be balanced for statistical purposes but study discipline, gender and posture will not be controlled but simply recorded for descriptive statistics and emergent correlation or association outcomes. In each of these settings, the mobile ITS prototype – tablet - employs the use of the two sensors (a camera

to monitor the user's eye gazes or face orientation and a Bluetooth physiological wrist monitor data).

The wrist-worn Bluetooth heart rate monitor captures electrodermal activity (EDA) and heart beats per minute data via newly researched optical technology (WO2013042070 A1, 2013) without the need for an intrusive chest strap. The camera will monitor the user's eye gazes and face orientation towards the tablet utilizing onboard functionality offered by the Qualcomm CPU's and the Snapdragon SDK for Android (Qualcomm, 2017).

The research will be validated through the use of triangulation. Triangulation allows the results of a study to be validated using distinct data sources (Hussein, 2009). Triangulation of the multiple sources including:

- Sources taken throughout the two sessions:
    - Puzzle game scores
    - Face detection
    - Heart rate captured
    - Electrodermal Activity
    - Skin Temperature
    - External camera recording the sessions.
- User Satisfaction Survey taken at the conclusion of the session
- Self-reported assessments during the play session

In our study, our distinct data sources would include automated measurements gathered from the tablet, user surveys throughout the process, and researcher observation. The study will ascertain the quality of eye gaze (Nakano & Ishii, 2010) measurements and heart rate (Galán & Beal, 2012) readings as it correlates with user engagement. Additionally, learning effectiveness can possibly be measured from user questionnaires, user feedback, and differences in scores throughout the session.

Test Subjects

Test subjects would be individuals on a university campus. These subjects would include typical demographic of the university, such as, study discipline (e.g. engineering, art, business, etc.) age, gender, and ethnicity but volunteers resulting in a nonprobability sampling as described at:

- http://www.socialresearchmethods.net/kb/sampnon.php
- http://dissertation.laerd.com/non-probability-sampling.php#step4
- https://explorable.com/convenience-sampling
- http://www.statisticsconsultant.com/dissertation-advice/what-is-the-smallest-sample-size-i-can-use-for-my-study/

There may be an underrepresented bias for those who are either too busy, or do not care to participate in the study.

For this study, we have decided to enable mobile sensors for all participants, leaving the

ergonomic position as the independent variable that differentiates the different groups.

Table 4 introduces the different experiment groups which will be studied. The groups

will be defined by how the users will be using the tablet application. The control group

would be a group of users that used a similar application in a traditional desktop

computing environment. Due to limitation of 100 student participants, in order to have

enough statistical power and resolution, the traditional desktop computing group was

removed (closely resembling the sitting group 1) and the study was focused into three

tablet application groups: on a task chair, reclined on a sofa, or left standing. In order to

reduce the number of factors, all three groups would be located within a classroom.

Table 4: Research Group Categorization

Group Description	Group Number	Notes
Seated on a Task Chair	Group 1	Resembling a traditional control group, but with a tablet.
Reclined on Sofa	Group 2	Similar to how people would use a tablet.
Standing	Group 3	Similar to how a user might interact with a tablet in a store or museum.

Use of a camera sensor

Studies such as the one conducted by D'Mello et al. (2012), has shown that cameras and

gaze detection is important in ITS's and student engagement. By using the onboard

camera found on tablets, the idea is to see if the passive mobile sensor (the camera) can

be used effectively to increase the level of engagement of the user. This is opposed to the

use of traditional cameras that are in the face of the user, as those used in the study by

Arroyo et. al (2009). Cameras may or may not make people nervous, and by using a camera that is not so inconspicuous, may allow people to act more natural.

Use of a Bluetooth heart rate monitor

Literature review conducted by McQuiggan, Mott, and Lester (2008) has shown that heart rate has already been used to adjust difficulty levels in games, "detect frustration and stress", and "monitor anxiety". Likewise, their review has collected different studies that use EDA to "sense user affective states, student frustration for learning companion adaptation, frustration for life-like character adaptation in a mathematical game, and multiple user emotions in an education game" (Mcquiggan et al., 2008). Although not directly related to learning, skin temperature has been shown to illustrate the difference between a user's relaxed and stressed state (Zhai & Barreto, 2006).

Recently, the technology that was used most often in heart rate monitors required the user to strap the monitor across their chest, making sure the contact touches the skin and doesn't completely dry out. This type of technology may prove to be an inconvenience for athletes and uncomfortable for non-physical activities. However, by moving from the chest-strap monitoring technology to an optical monitoring technology, the heart rate monitor can be fashioned into a wristband that closely resembles a digital watch. If the user is already accustomed to wearing a wristwatch, the wristband form factor lets people feel comfortable as opposed to wearing the sensor technology underneath their clothes. Similarly, with the increased sophistication of these devices, it's also possible to extract EDA and skin temperature data at the same time.

Location/Environment of User

The research effort will also vary the posture of the user, which allows us to determine the effectiveness of mobile sensors in different settings. In the study, the user will either be seated in an armless task chair without a desk, reclined on a sofa, or left standing. This allows us to explore the possibilities that mobility offers by studying different use case scenarios.

Dependent Variables

By changing the posture of the test subjects, we will obtain the dependent variables for the level of engagement of the participant, and the change in scores throughout the course of the study.

Delay between game moves by the participant

The intent of this research is to determine how various passive mobile sensors can be possibly used to gauge the level of the participant's engagement on a mobile platform. One goal would be to determine when a user begins to lose interest and provides this information to an ITS, so it can adjust its tutoring strategy. Future research can study the correlation between the frequency of touch screen gestures and user engagement as they interact with the application, if such a correlation exists.

Difference in high scores taken during the session

As the user begins to use the mobile application, it is expected there will be a learning curve as they understand the interface and rules. From this understanding, the user will be able to start to develop effective strategies which will help them grow their score.

However, what is the impact on the scores if the user has begun to lose interest? By measuring the changes in scores, we can obtain a different perspective on their engagement. Scores are important in puzzle games (and thus, in this study) since this is one of the primary mechanisms that the game has to provide feedback to the user on their performance (Marshall, Coyle, Wilson, & Callaghan, 2013).

Instrumentation

The research study will use numerous instruments to collect statistical data. Each instrument captures a different perspective of the study and the synergy between all instruments provides an overall picture.

Demographic Questionnaire

The demographic questionnaire provides general background information on the study participant, such as age, gender, study discipline, technological background, and any preference to specific genres of video games and puzzles. In order to protect the user's identity, each user is assigned a randomly generated participant code. The participant code will be used to identify the data throughout the study. However, if the need arises to tie the participant codes with personally identifiable information, this index file will be kept on a separate system, not accessible from any network and encrypted with a 128-bit encryption algorithm.

Usage data from the Mobile Application

The mobile application is the main vehicle of interaction between the system and the user. Thus, there are many different metrics that can be captured here, such as: when

touch interactions happen, the delay between interactions and the frequency of gestures the user has made. The usage data helps paint the picture as to the user's level of confidence.

Engagement Scores

The application will keep track of the scores over time to try to determine how effective the user is in developing successful strategies. When these scores are combined with other data, we can infer a level of engagement and generate engagement scores.

Satisfaction Survey from Users

At the conclusion of the session, the user is presented with a survey where they can express what they felt about various aspects of the study, such as: perceived effectiveness of the training, sense of comfort, and how engaged they felt during the session.

Affective Slider

Before the practice session and after the conclusion of the live session, the subject will be presented the Affective Slider (AS) developed by Betella and Verschure (2016). The Affective Slider was developed as an evolution to the popular Self-Assessment Manikin (SAM) developed by Bradley and Lang (1994). However, since SAM is made up of graphics that are more than twenty years old, the graphics are not easily understood by the study participants (Betella & Verschure, 2016, p. 2). Thus, the AS utilizes two sliders that tracks arousal and pleasure, and eschews a third slider which SAM captures against the dominance emotion (Betella & Verschure, 2016, p. 4).

External Camera Observations

By keeping the researcher actively observing the session, obvious anomalies with the

participants could be noted and captured as part of the study's collected data. Since the

researcher isn't actively interacting with the user, there is very little risk of introducing

researcher bias. However, it has been suggested that an external camera should be used

which will provide another data point to validate the study.

Research Procedures

The students participating in the study will be given access to a tablet with the mobile

application. After the student has used the application, they are provided with a

satisfaction survey where they rate how they feel about the experience. Using the scores

obtained from the mobile application, the high scores are correlated with the other

statistics obtained from the mobile application and from the satisfaction survey.

The mobile application utilizes the onboard camera and a paired Bluetooth heart rate

monitor as sensory inputs from the student. It also interacts with an application server

which currently serves as a repository for data obtained via the tablet during the session.

Figure 4 shows the component diagram for the mobile application. From this diagram,

all of the interactions from external sources and various internal subcomponents are

depicted. Libraries for the camera and Bluetooth sensor are libraries that are already part

of the Android operating system, or part of the onboard driver that manages the hardware,

such as the camera manufactured by Qualcomm (Qualcomm, 2017). Furthermore, while

various sensor data is being captured, this information is saved and can be reported back

to a server for safe keeping. The application server could host other applications, such as

an Intelligent Tutoring System that could send information back to the mobile application
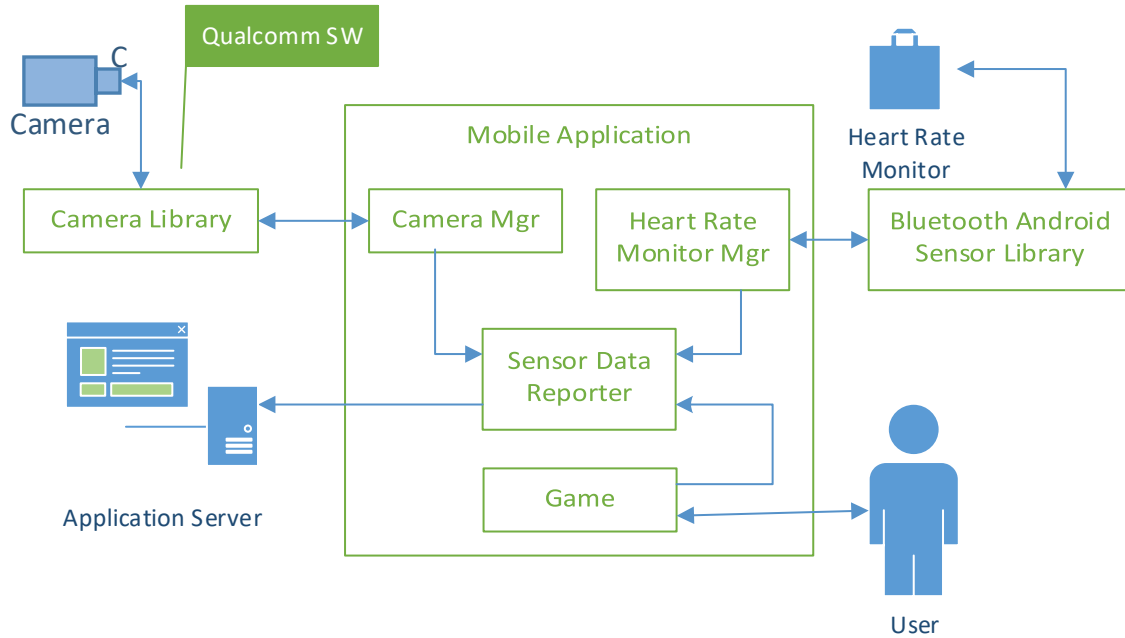
if the functionality was supported.

Figure 4: Mobile Application Component Diagram

In order to provide the functionality required, the mobile application is made up of

various sub-components:

1. Camera Manager – Manages all interactions with the camera library and provides

    eye and gaze sensor information to the Sensor Data Reporter.

2. Heart Rate Monitor Manager – Manages all interactions with the heart rate

    monitor and provides the information to the Sensor Data Reporter.

3. Sensor Data Reporter – Receives various types of sensor information and reports

    this data to the application server for recording and further processing.

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4. Game – Component responsible for the interaction logic with the user. This component sends information to the Sensor Data Reporter and communicates with the user via physical interaction.

Figure 5 details the composition of the application server, and its external interactions. As evident from Figure 5, the application server will be running the sensor data processor and database. The intent of the application server is to be a repository of metrics to be analyzed at the conclusion of the study.
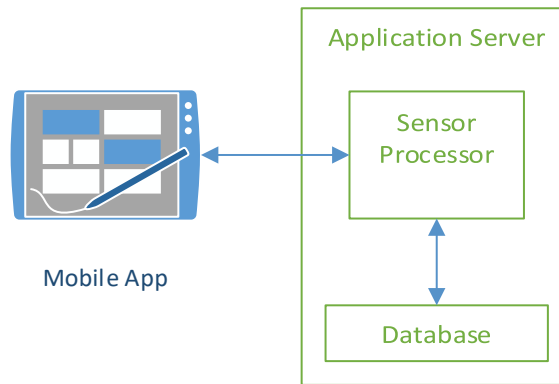

Figure 5: Computer Component Diagram

In order to reduce the risk of any unknowns, an early prototype (or proof-of-concept) has been developed of the mobile application as it communicates with a Bluetooth heartrate sensor (Scosche Rhythm+), on-board hardware camera, and with the GIFT server. The hardware running the mobile application is the Nexus 7 tablet. As Figure 6 depicts, the mobile Intelligent Tutoring System, or mITS for short, has successfully detected the user's face and eyes, monitoring their heart rate, and sending and receiving messages from the GIFT server.
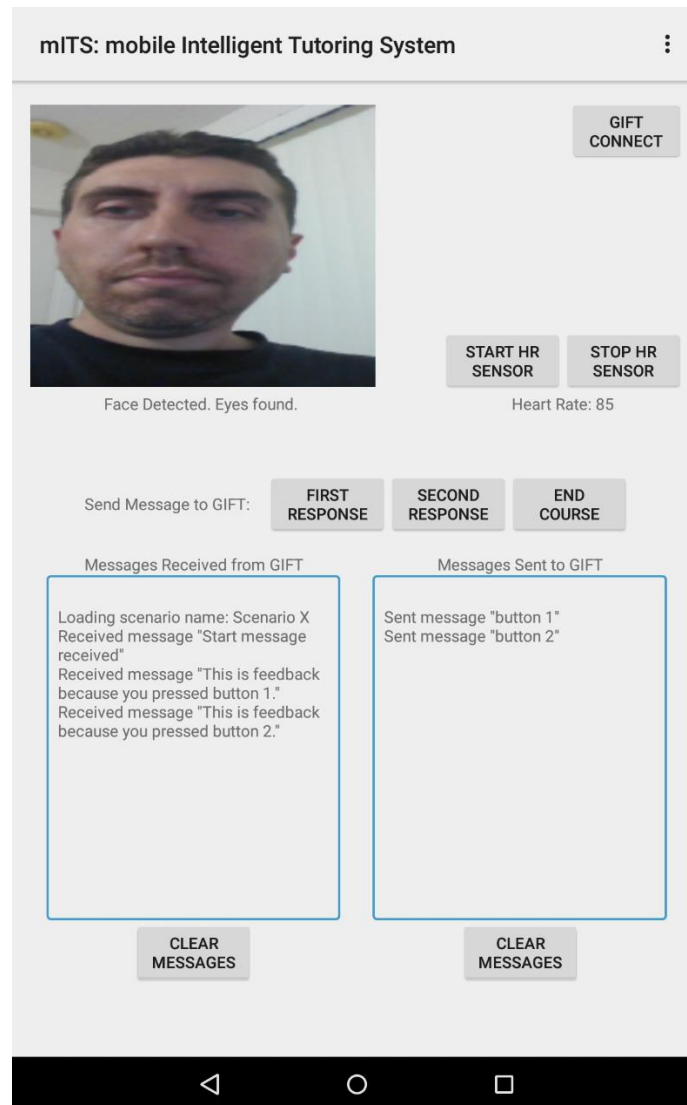
Figure 6: Screenshot of the mobile Intelligent Tutoring System

Before the study can commence, we would need to change the interface of the mITS and

insert a game in lieu of an ITS. Inserting a game simplifies the aspect of the study which

would require the generation of a curriculum and its appropriate multimedia. Therefore,

we can proceed to answer the research questions proposed in an earlier section. This

interface would also minimize the camera preview and hide the diagnostic information

that is currently exposed to the user. Ultimately, mITS will be showing only UI elements that are user-centric.

Data Collection

The collection of the data required to answer the research question and to support the hypothesis proposed, the data must be collected by a specific methodology. The methodology employed follows the research design that has been discussed earlier in various stages. Afterwards, specific aspects of the data types, self-reported versus system-observed are discussed.

Study Procedure

Obtaining Participants and Consent

Using the UCF Psychology SONA participant pool, the researcher will offer timeslots where the participants can schedule themselves. Upon arriving at the designated study location, the researcher will explain the details of the study and what they can expect. The researcher will explain that there will not be any uniquely identifying personal information taken from the participant, and they will be assigned a random generated id, within the application, to be solely used for record keeping. At this point, the participant will acknowledge the informed consent and be provided with a study overview paperwork for their records.

Participant Setup and Research Group Assignment

Upon providing consent, the participant is set up with the wrist worn monitoring strap in an indoor physical setting. The application on the tablet will be set up for a new

participant, which will be configured to a specific ergonomic position, per the research

study design. While the application and participant are setting up, the sensors are

actively monitoring the participant to determine that individual's baseline reading, along

with room temperature and ambient noise level readings.

Have participant use application on tablet

Once the participant is ready to begin, the application will present the game UI to the

participant and be allowed to interact with the game. The game will pay close attention

to the scores in the beginning of the session versus those near the end. Throughout the

session, sensor readings, researcher observations, and other metrics will be stored for

later analysis.

Wrapping up study

After the session, the participant is allowed to remove their wrist-worn monitoring strap

and is provided a chance to give feedback on their experience via paperwork or via the

tablet application. The application will capture the responses as part of an additional

section of the tablet application and associate it with the training session.

Self-Reported Measures

For self-reported measures, the study will make use of user feedback surveys from before

and after the sessions that will reflect general background information, how they feel

about the system, and if they feel if it was engaging. The surveys will be set up using a

Likert-scale for the responses.

System Observed Measures

This study will employ more system-observed measures through the use of sensors and other instrumentation. Face detection measurements will be determined by the system whenever it detects that the user is actively looking at the screen. The study will determine if there is any correlation between when the user is engaged with the system and the time elapsed looking away from the screen.

Furthermore, while using the system, heart beat and electrodermal activity measurements will be taken every second (as the device will allow). With such a high frequency, this measurement could be analyzed for later conclusions. There is also another set of measurements that can be inferred from the scores and gesture frequencies.

Assumptions of Study

In this study, the emphasis is upon the mobile device and the interactions between the application and user. Therefore, the study assumes that there is a strong and stable wireless connection for metrics capture. This removes any requirement of handling the case where the device must manage its loss of network connectivity.

Summary

This study will measure the feasibility of integrating mobile sensors with an Android application with an ITS. By obtaining a variety of different physiological signals, eye gazes, and usage metrics, we can start to determine if this information can be used to drive ITS engagement on a mobile platform.

CHAPTER FOUR: DATA AND ANALYSIS

After obtaining support from the dissertation committee to proceed with the study proposed in the third chapter, hardware was procured, and software was developed to support the study. The study was then executed with participants followed by a phase of statistical analysis described later in this chapter.

Equipment Used

Figure 7 shows the specific equipment obtained in order to support the study: heart rate monitor Empatica E4 (A), camcorder Canon VIXIA HF R800 (B) with five-foot tripod (D), and the seven-inch tablet Nexus 7 (2013) (C) with supporting adjustable tablet stand (E). The Empatica E4 was procured with assistance from UCF, and the camcorder/tripod was added based upon the recommendation of the committee during the proposal.

Figure 7: Equipment used in Study

mITS to mITS2048 Development

As discussed in chapter 3, the decision was made to replace the sample course in the

prototype developed for the proposal (mITS), and to begin development on mITS2048

which required the integration of the puzzle game 2048. This was done in order to

reduce the scope of the study to focus on the reliability of mobile sensors, and away from

the development of a suitable and validated ITS course. Furthermore, the inclusion of a

cloud-hosted ITS would have required additional encrypting of personally identifiable

information (PII) and ensuring the cloud-hosted solution has an appropriate level of security.

From a software perspective, the source code for 2048 (Cirulli, 2017) is freely available on GitHub which allows us to verify that malicious code is not introduced into the application. Since the puzzle game is self-contained, for development purposes, it was best to view it as a separate module when inserting it into the mITS framework. Once integrated, software code had to be modified to foster two-way communication to the Android app and to be able to extract events and tracking data while the game session was active, such as gestures, score, and session elapsed time. Other modifications include the introduction of the different session, a running count-down timer, and spacing to fit the camera preview. Thankfully, no extra work had to be performed in order to convert the game's keyboard controls to a touch-friendly interface as the hardware naturally converted this input automatically.

Since the focus of mITS2048 was on the feasibility and reliability of using sensors on a mobile platform, the connection to the server-side ITS, GIFT, was temporarily severed. The prototype GIFT connection code still exists within the application but is not accessible or active in mITS2048. Furthermore, without this server-side connection, the captured metrics from the study had to remain on the tablet, until the data was moved to a secure location. Establishing a new server connection for metrics capture provided additional technical logistics such as securing hardware computing resources which can protect the captured data. Keeping the captured study data local alleviated any potential

concerns the IRB may have had about any personally identifiable information residing in the cloud.

With respect to the Bluetooth heartrate monitor, the hardware was upgraded from the Scosche Rhythm+ to the Empatica E4. The Empatica E4 offers better resolution and frequency of biometric data (Empatica, 2016). Integration of the Empatica E4 required the use of vendor furnished Android API and after a short time, was properly integrated into mITS2048.

The on-board camera functionality was unchanged between mITS and mITS2048 with the exception of writing to log files whenever the application detected and lost track of the participant's eyes. Due to technical limitations with mITS2048 and the tablet's camera API, it was not feasible to track facial expressions, which rules out any descriptive statistics for research question 2.

2048 Gameplay Overview

The tile-based puzzle game 2048 (Cirulli, 2017) was chosen due to its simple gameplay controls and easy-to-understand rules. Upon the start of a new game, the player is presented with two tiles assigned values of 2 or 4. The player will now select a cardinal direction which will affect the entire board, and all tiles are moved along that direction, removing any empty spaces as the tiles are stacked upon other tiles. If any tiles are assigned the same value as they are stacked along that chosen cardinal direction, the two tiles are combined as the sum of the tiles.

Since tiles can only start with 2 or 4 and can only be combined with tiles with values that are equal to each other, only tiles with base 2 numbers can be generated (2, 4, 8, 16, etc.). Once a direction has been chosen, the tile combination phase is complete, a newly generated tile (assigned a value of 2 or 4) is placed on an empty tile. Each move can have multiple tile combination, and per each successful tile combination, the value of the new tile is added to the player score. The game is complete when there aren't any empty places remaining on the board.

<div align="center">Overview of the Participation Study with mITS2048 Walkthrough</div>

With the approval of the UCF IRB, the study was conducted utilizing participants from the UCF Psychology Sona System. The UCF Psychology Sona System allows students enrolled in Psychology courses to sign up for online and in person studies in exchange for credits which reduces the amount of written assignments required by the student. The participants committed to specific timeslots over the course of a few weeks between June and July of 2017 where they met with a researcher. As they arrived, the researcher discussed the informed consent per IRB instructions and provided a brief explanation of the study and its rationale.

While the participant was being equipped with the Empatica E4 wrist-worn heartrate monitor on their dominant hand, the researcher started up the tablet application in order to determine which group the participant will be assigned, as shown in Figure 8: standing (behind podium (A)), lounging (on sofa (B)), or sitting (at a desk (C)).
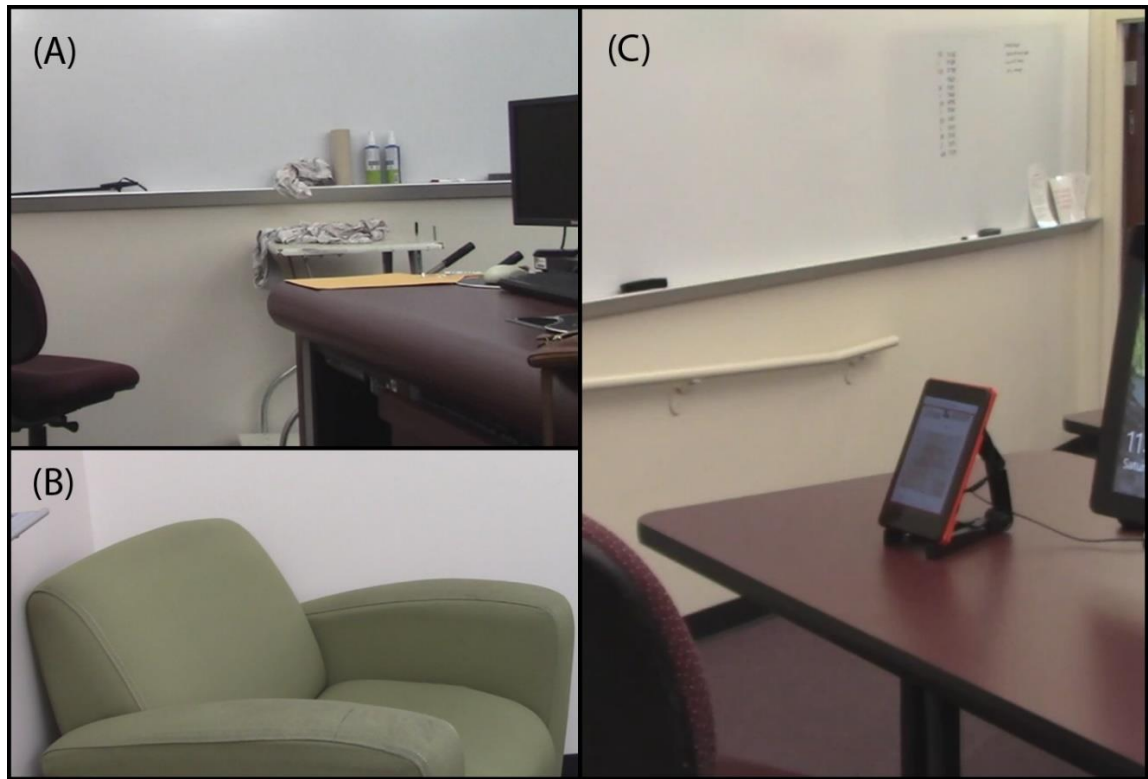
Figure 8: Locations Exhibiting Different Ergonomic Positions in the Study

As the participant moves to their randomly assigned location, a video camera (Canon

VIXIA HF R800 with 5' tripod) is positioned to record the study. The sitting group

comes equipped with a tabletop stand (AmazonBasics Adjustable Tablet Stand) that

maintains the tablet in a sturdy and stationary position. The lounging group were

directed to a sofa which allows the participant to sit while they held onto the tablet.

Whereas the podium requires the participant to remain standing throughout the study

while they interact with the tablet application. In Figure 8, the standing group faced the

external camera so that the podium stand was behind them on their left-hand side.

The first thing each participant was required to do was fill out a short questionnaire on

the tablet as depicted by Figure 9. The questionnaire consisted of demographic questions

such as age, gender, and study discipline (major). Using a five-point Likert scale, the

questionnaire also asked for familiarity of computers, tablets, and fitness bands. Lastly,

with a seven-point Likert scale, the participant was asked about their level of enjoyment

when playing the following video game genres: action (Donkey Kong), adventure

(Zelda), puzzle (Tetris), roleplaying (Final Fantasy), simulation (Flight Simulator), sports

(Madden), and strategy games (Civilization).

Figure 9: Pre-experiment Questionnaire Screenshot

Once the demographic questionnaire has been completed, a self-assessment survey was

displayed to the user as shown in Figure 10. The self-assessment consists of a slider

between bored and excited, and another slider between sad and happy. With respect to the self-assessment survey, it makes use of the affective slider (Betella & Verschure, 2016) which is licensed under the Creative Commons license CC BY-SA 4.0. The license requires us to provide attribution (done by citation) and a link to the license (Creative Commons, 2018). The images were not changed when included in mITS2048, therefore the ShareAlike clause of the license would not apply to this study.
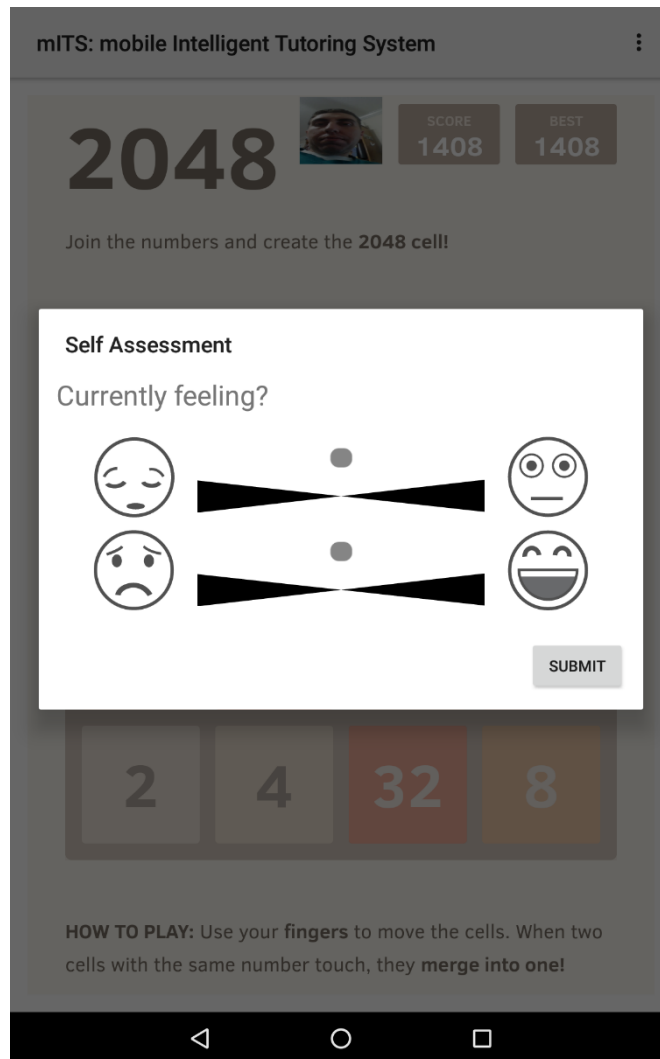
Figure 10: Self-assessment Survey

After the self-assessment is complete, the practice session is presented to the user and

will begin once the start button is pushed as shown in Figure 11.
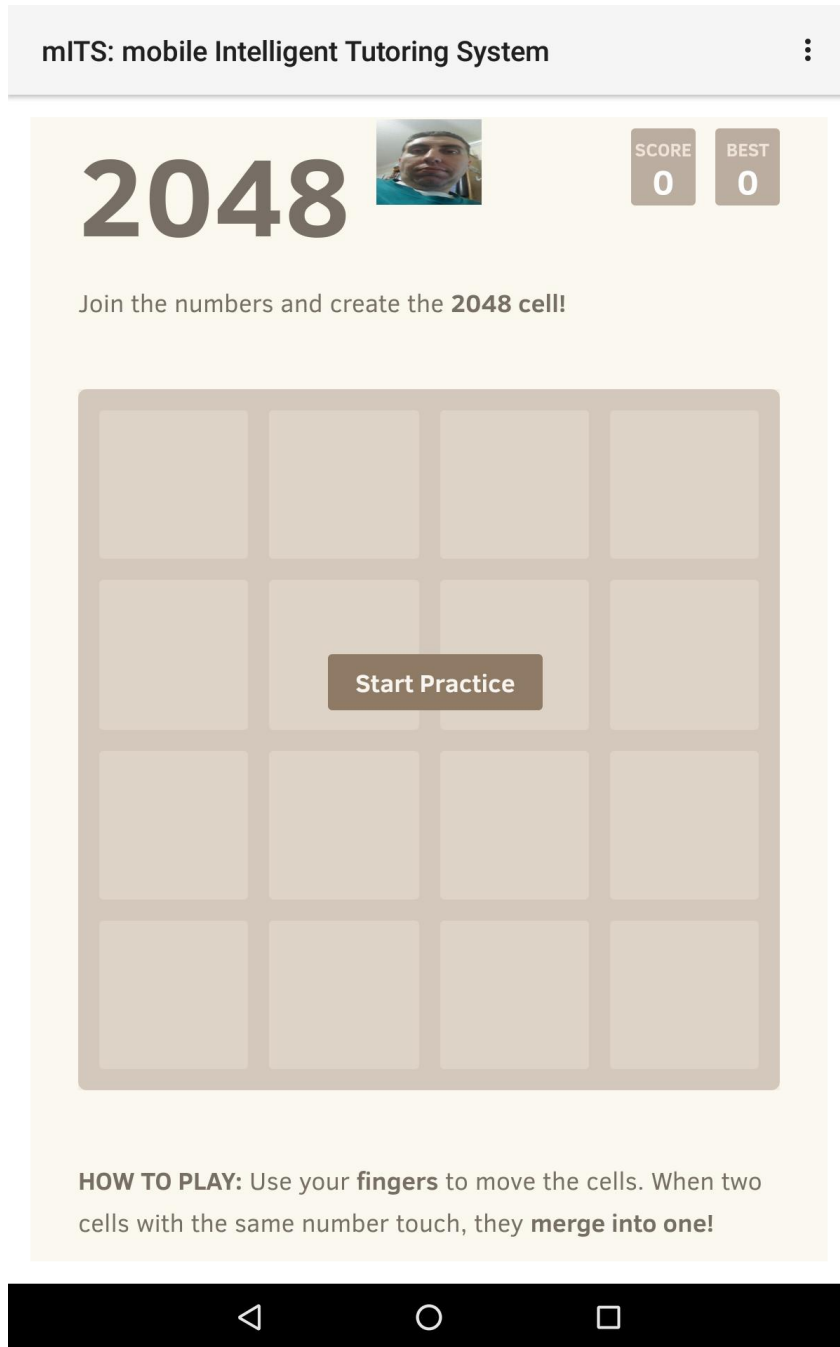
Figure 11: Start Practice

The participant will have up to seven minutes or until they run out of moves to get a feel

for how the game is played as shown in Figure 12.
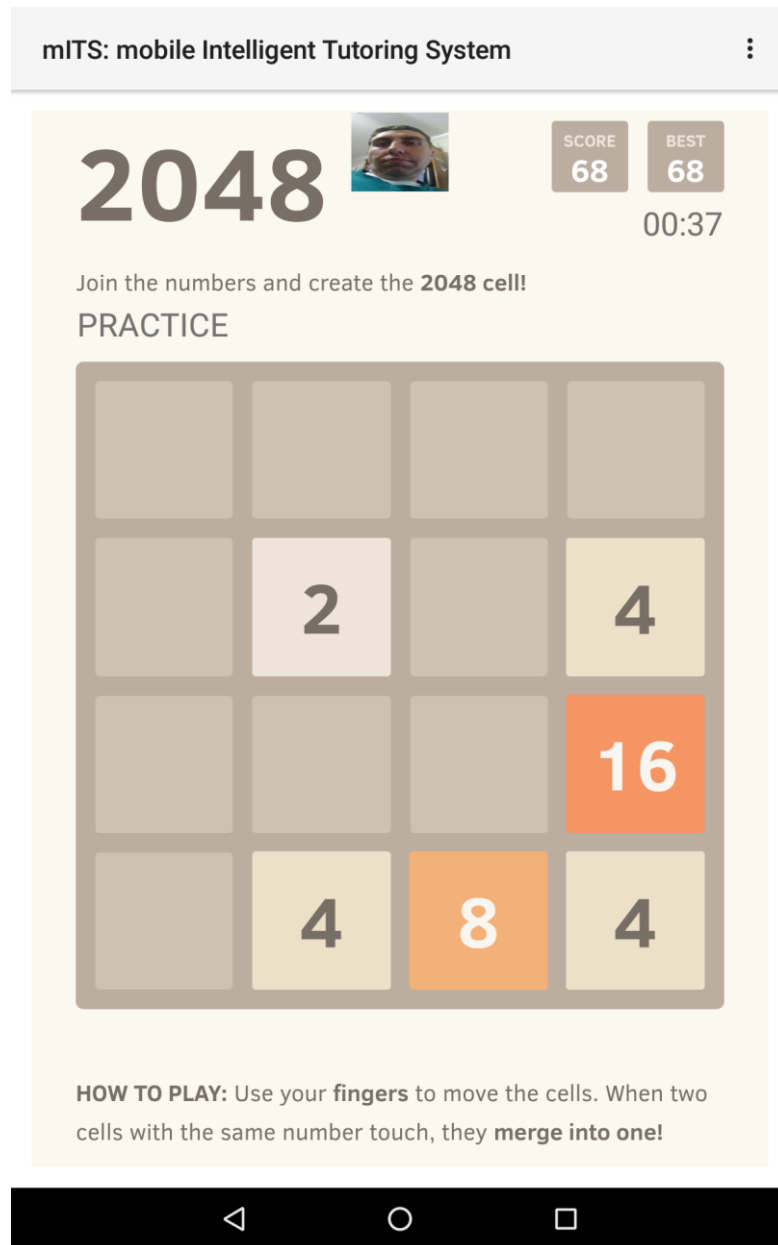
Figure 12: Practice Session

Similarly, at the conclusion of the practice session, the live session is started once the start button is pushed as shown in Figure 13.
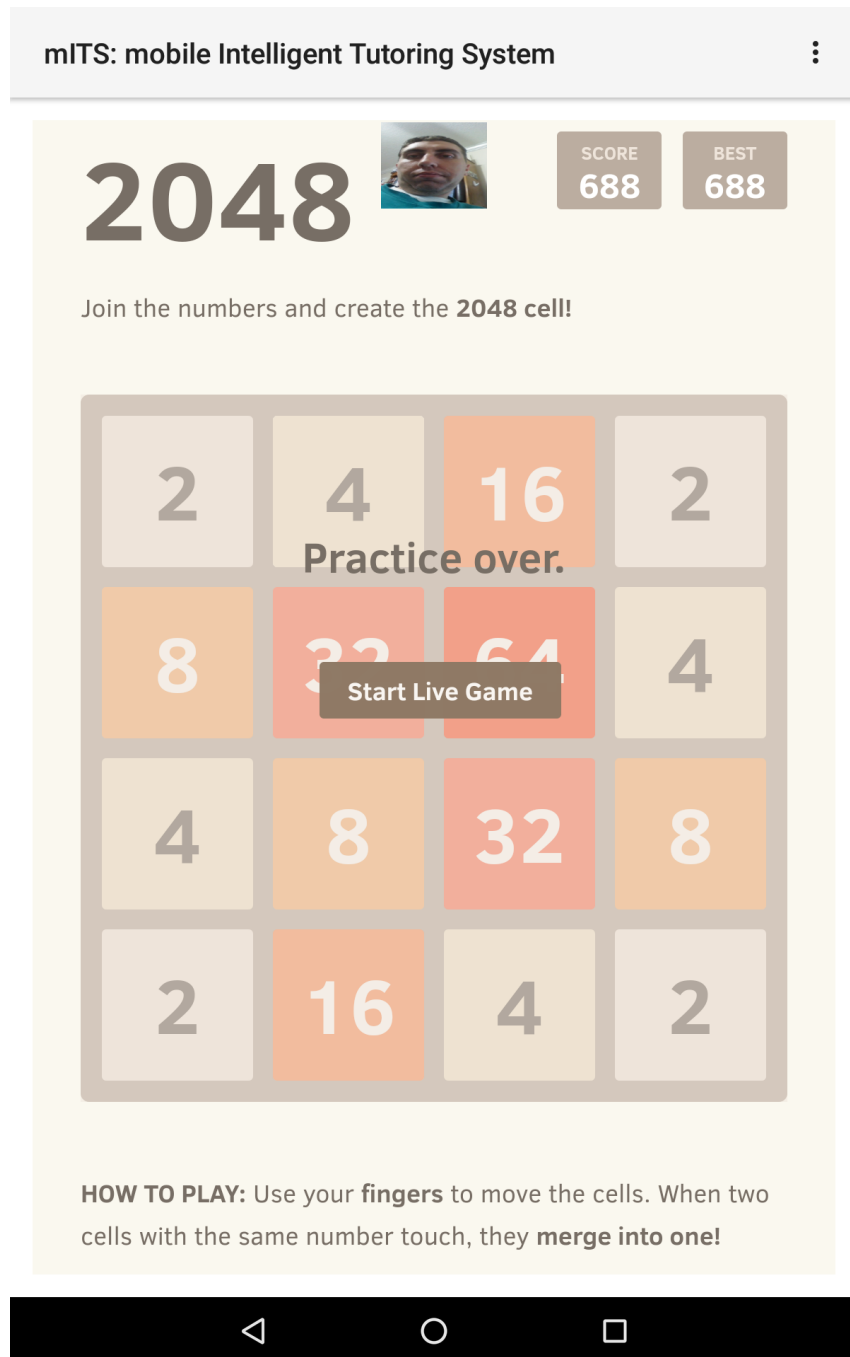
Figure 13: Start Live Session

Again, the user will have at most seven minutes or until they run out of moves to try to achieve the highest score possible.

Once the live session has completed, the user is once again presented with the same emotional self-assessment (like Figure 10), and finally with a satisfaction survey depicted by Figure 14. The satisfaction survey is aimed to determine how comfortable the participant was with: the wrist-worn band, tablet, game, game controls, physical environment, and the overall experience using a seven-point Likert scale.

Figure 14: User Satisfaction Questionnaire

Once all surveys are complete, the researcher closes the tablet application and helps the

participant remove the wristband. Per the agreement of the UCF Psychology Sona

system, the researcher provides the participant with an anonymous survey regarding their

experiences that would be delivered to the Psychology Department's main office.

Shortly thereafter, the participant is credited with the Psychology Sona system with the appropriate participation credit.

Study Data Processor

At the conclusion of the study, due to the way mITS (and similarly mITS2048) was designed, each data source produced a comma-separated values (CSV) file consisting of two columns for self-reported data and three columns for system-observed data. Self-reported data simply has the data name and the data value in a numerical format. During post processing, the numerical value is associated with the label that represents the value in the survey. The bulk of the gathered data is system-reported data which consists of data name, data value, and the time that exact piece of information was recorded. There are seven data files as described in Table 5.

Table 5: Raw Data Files

Filename	Data Description	Data Type
2048App.csv	2048 events such as board state, score, game starts and ends.	System Observed
camera.csv	The specific time when the camera as detected and lost the participant's face.	System Observed
demoQuest.csv	Participant responses to the demographic questionnaire.	Self-Reported
Empatica.csv	Feed of physiological data from the Empatica E4 wrist-band including heart rate, EDA, skin temperature, and any detected acceleration on the device.	System Observed
selfAssessment.csv	Participant responses to the self-assessment slider.	Self-Reported
TouchListener.csv	The specific times when the tablet has detected the participant has started and finished their gesture.	System Observed
userSatisfaction.csv	Participant responses to the user satisfaction questionnaire.	Self-Reported

The Study Data Processor (SDP) is a C# application tasked with processing every participant's unique raw data files and combining them into one combined csv. Figure 15 shows the class diagram of the specific data processor for each type of file. Each data processor has a specific implementation on how to obtain the study data, based upon the type of file. For example, the touch data processor has to process a data range, whereas the camera data processor has to fill in data between the face detected and face lost entries. Furthermore, a handful of processor also includes functionality to generate metrics such as average, mean, and so forth. By running this application, it simplified the statistical analysis within JMP later and the generation of participant graphs, described later.
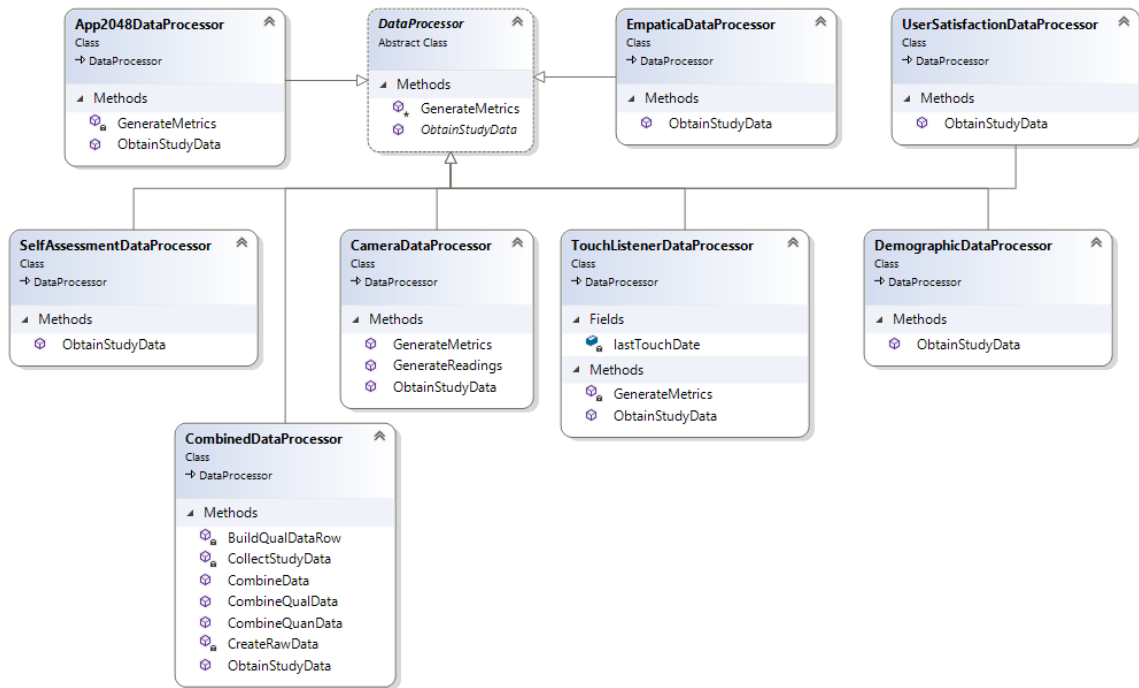
Figure 15: Study Data Processor: Data Processor Class Diagrams

Once each participant has their own combined file, the unique data processor

CombinedDataProcessor's role is to read in all the participant's combined files and make

one large aggregated data csv file. The large combined csv includes every participant's

qualitative responses to their questionnaires which puts the data in one place for JMP

analysis. For simplicity, the aggregated data file also includes generated metrics from

each participant such as average score, average face detected time, and so forth.

Demographic Data

The study leveraged from the participant pool from the UCF Psychology Sona system

during the Summer 2017 term at the University of Central Florida. During the summer

semester, the participant pool was entirely made up of undergraduate students taking

general psychology classes, thus providing a representative sample of the UCF undergraduate student body. The study was able to maximize its participant allotment of 100 students per the IRB's approval. With these 100 students, obtaining a large effect size f=0.4, α=0.05, and with 3 groups produces a post-hoc power of 95.08%.

Per Figure 16, UCF's undergraduate population is composed of 54.1% female and 45.8% male (UCF, 2017), and similarly, the study received more female participants than male participants.
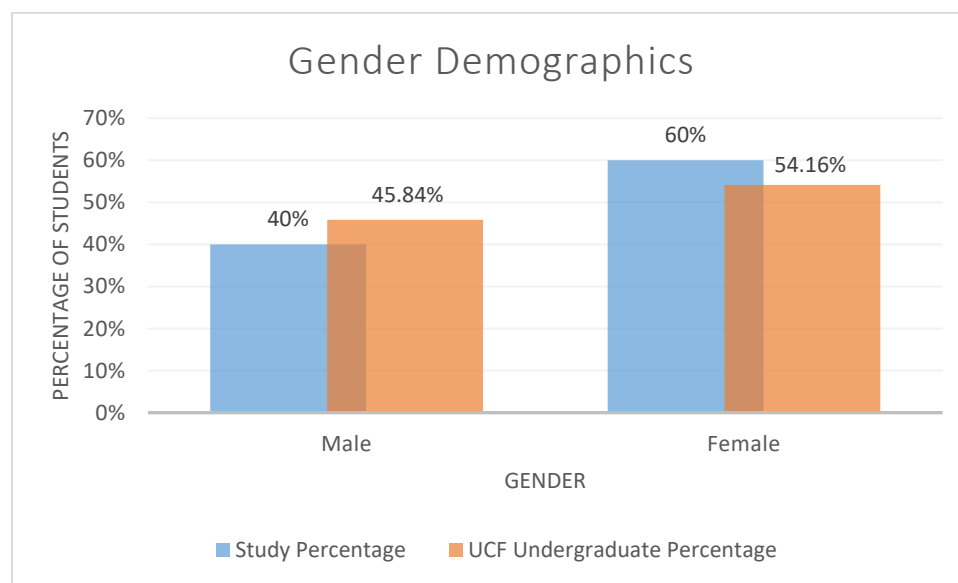

Figure 16: Gender Demographics Comparison

Furthermore, Table 6 shows the ages of the participants and it shows that there are more 18-year-old participants than any other group. Although the exact course was not captured per participant, there's a good chance that these students are enrolled in a general psychology course usually taken by first and second year students offered in the summer.

Table 6: Participant Age

Participant Age	Participant Number	Percentage of Participants
18 years old	82	82%
19 years old	11	11%
20 years old	3	3%
21 years old or older	4	4%

Figure 17 depicts the difference between the UCF undergraduate percentage by college versus the response received from the study. From the figure, the number of students from the nursing college appear to be overrepresented in the study by 11%, but the other colleges tend to follow the UCF undergraduate percentage (UCF, 2017).
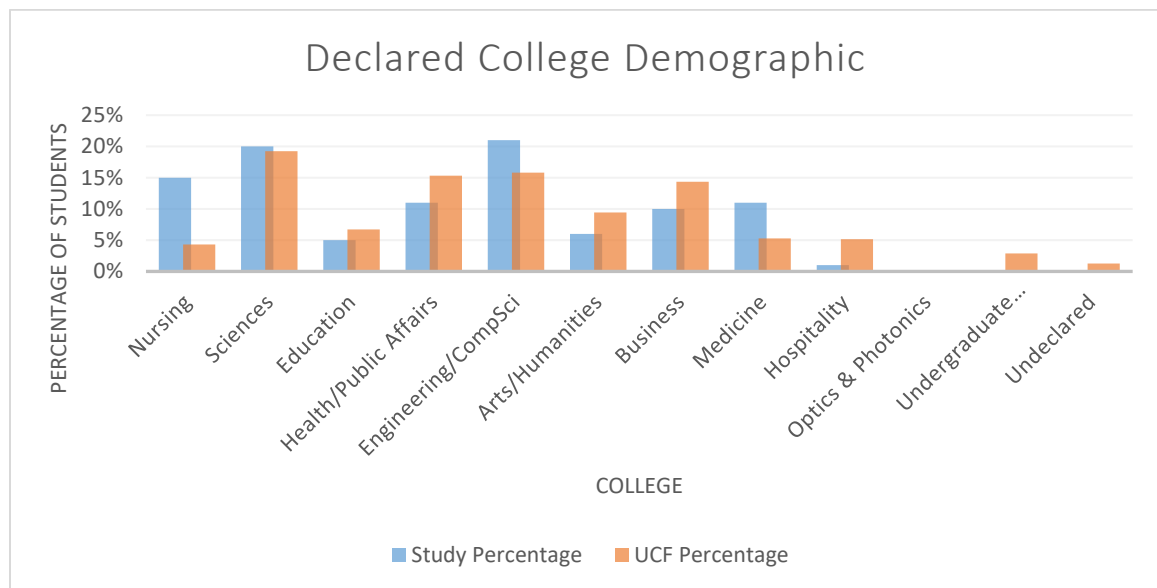

Figure 17: Declared College Demographic Comparison (UCF, 2017)

User Reported Questionnaire Findings

All descriptive and inferential statistics and related symbols reported below are from SAS JMP Pro 13 (Goos & Meintrup, 2016; SAS Institute, 2016). Table 7 indicates the self-assessment by each participant for their familiarity with computer, tablet, and fitness

band interfaces. Consistent with Likert scales prevalent in many medical/psychology

surveys (Yates, Orgeta, Leung, Spector, & Orrell, 2016), the range of familiarity

responses for computers, tablets, and fitness band interfaces are: "Not at all Familiar" =

0, "Slightly Familiar" = 1, "Somewhat Familiar" = 2, "Moderately Familiar" = 3 and

"Extremely Familiar" = 4. The range of responses for level of enjoyment of a video

game genre are: "Strongly Disagree" = -3, "Disagree" = -2, "Somewhat Disagree" = -1,

"Neither Agree or Disagree" = 0, "Somewhat Agree" = 1, "Agree" = 2 and "Strongly

Agree" = 3. Responses indicating "Not Familiar with this Type" are recorded as 4.

Shapiro-Wilk tests on their familiarity responses indicates that the data is not normally

distributed: computers (w=0.86, p=<0.001), tablets (w=0.88, p=<0.001) and fitness bands

(w=0.85, p=<0.001).

Table 7: Technology Familiarity Responses

Familiarity Technology	Not at all Familiar (0)	Slightly Familiar (1)	Somewhat Familiar (2)	Moderately Familiar (3)	Extremely Familiar (4)	Average (Scale 0 to 4)	Statistically Different than 0.
Computer	3	10	20	37	30	2.81	Yes
Tablet	3	13	28	44	12	2.49	Yes
Fitness Band	37	27	16	17	3	1.22	Yes

Furthermore, Wilcoxon signed rank tests reports statistical evidence (using JMP reported

S test statistic) that participants are familiar with computers (S=2522, p=<0.0001), tablet

(S=2522, p=<0.0001), and fitness band (S=2173.5, p=<0.0001). Figure 18 indicates

participants expressed different levels of familiarity with computers, tablets and fitness

bands further corroborated by the Kruskal-Wallis test (H(2)=80.7, p<=0.0001).
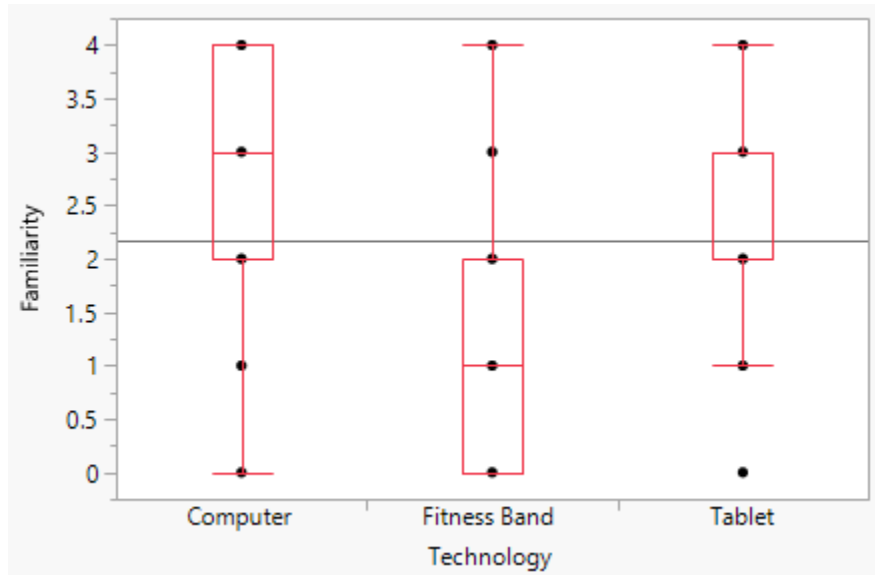
Figure 18: Level of familiarity of subjects between Computers, Fitness Band, and Tablet "Nonparametric Comparisons for Each Pair Using Wilcoxon Method" and taking into account Bonferroni corrections for 3 groups (.0167) indicates levels of familiarity between pairs of technology statistically differ: tablet/fitness band (using a U estimation of normality, Z=7.05, p=<0.001), computer/fitness band (Z=-8, p=<.0001), and tablet/computer (Z=-2.46, p=0.0138). To insure student assignment to posture groups was not biased by technology familiarity, an examination of familiarity levels by posture assignment treatments indicated no difference: computers (H(2)=5.02, p=0.081), tablets (H(2)=1.57, p=0.46), and fitness bands (H(2)=2.1, p=0.35).

Table 8 indicates subject self-assessed familiarity (columns two and three) with video game genres and if familiar with a genre, the level of enjoyment of that genre (columns four through eleven). In terms of familiarity with video game genres, there is statistical evidence that the vast majority of subjects are familiar with the seven different game

genres (H(6)=15.2, p=0.0187). If familiar, the level of subject enjoyment is affected by the game genre (H(6)=19.9, p=0.0028). If familiar with the genre, then Wilcoxon signed rank tests show the participants express enjoyment of that genre rather than express ambivalent at statistically significant levels (all genres present p=<.0001). JMP reporting test statistic S values (action=1744, adventure=1392, puzzle=1933, RPG=817, simulation=1623, sports=848, and strategy=1252) indicate puzzle games being among the most enjoyed genre.

Table 8: Enjoy Game Type Responses

Game Genre	Not Familiar	Familiar	Strongly Disagree (-3)	Disagree (-2)	Somewhat Disagree (-1)	Neither Agree or Disagree (0)	Somewhat Agree (1)	Agree (2)	Strongly Agree (3)	Mean (Scale -3 to 3)
Action	2	98	3	5	6	6	22	39	17	1.29
Adventure	10	90	4	6	4	8	13	31	24	1.32
Puzzle	3	97	2	3	4	9	19	41	19	1.46
RPG	13	87	1	13	8	13	19	22	11	0.68
Simulation	8	92	0	5	6	10	31	26	14	1.18
Sports	4	96	7	13	11	10	12	19	24	0.67
Strategy	7	93	3	7	9	9	21	36	8	0.91

Figure 19 illustrates the difference in the Affective Slider self-reported emotions at the start and end of the study. This data was obtained by utilizing the Affective Slider (shown in Appendix A), which is composed of two sliders between sleepiness versus awake and happiness versus sadness. The five groups are identified as: "Large Negative

Change" [-200 to -75), "Moderate Negative Change" [-75 to -20), "Little to No Change"

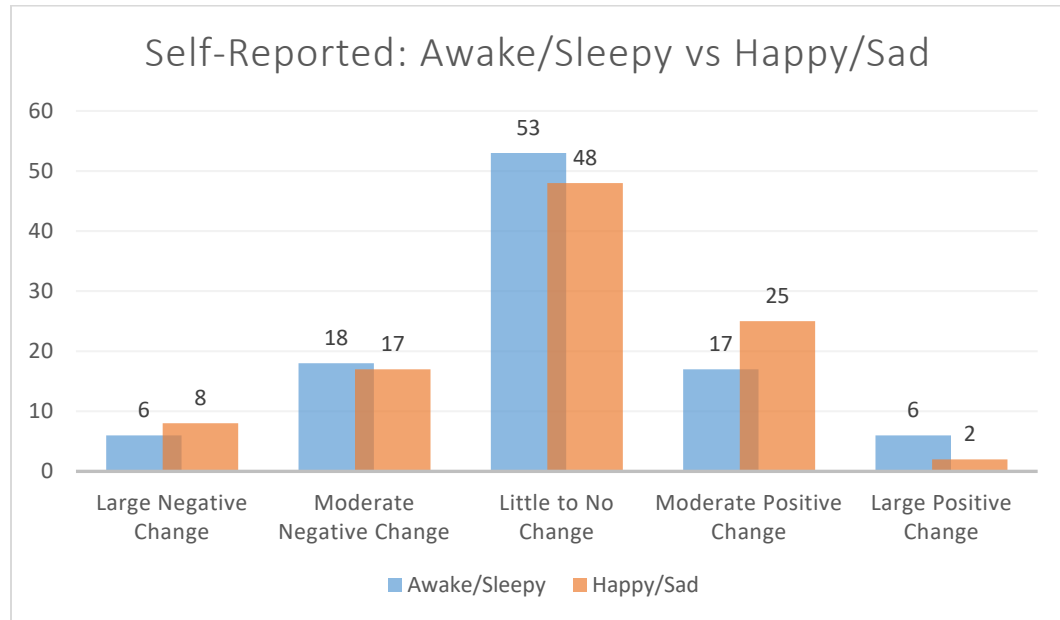[-20 to 20), "Moderate Positive Change" [20 to 75), "Large Positive Change" [75 to 200).

Figure 19: Self-Reported: Awake/Sleepy vs Happy/Sad

Performing Wilcoxon signed rank tests on the levels of not normally distributed

Awake/Sleepy pre-and-post state data (S=25, p=0.932) and Happy/Sad pre-and-post state

data (S=118, p=0.6882) suggests there is no statistical evidence that the study affected the

emotional state of the participant.

Respondents indicated varying levels of satisfaction with the experiment components

(Table 9 (H(5)=12.1, p=0.0334)) with participants expressing satisfaction rather than

ambivalence at statistically significant levels using the Wilcoxon signed rank test (all

components present p-values less than .0001, with JMP reporting values of: wrist band

S=2292, tablet S=2410, game S=2284, Game Controls S=2405, Physical Environment

S=2375, Overall S=2525).

Table 9: User Satisfaction Responses

Satisfaction Experiment Component	Completely Dissatisfied (-3)	Mostly Dissatisfied (-2)	Somewhat Dissatisfied (-1)	Neither Satisfied or Dissatisfied (0)	Somewhat Satisfied (1)	Mostly Satisfied (2)	Completely Satisfied (3)	Mean	Standard Deviation
Wrist Band	0	1	2	22	11	25	39	1.74	1.29
Tablet	1	0	2	4	18	38	37	2.00	1.07
Game	2	2	1	2	17	31	45	2.03	1.27
Game Controls	1	0	2	6	15	35	41	2.03	1.11
Environment	0	1	6	8	9	25	51	2.04	1.28
Overall Experience	0	0	0	0	15	33	52	2.37	0.73

Figure 20 and Figure 21 segregates Table 9 responses on environment and overall experience, respectively, by posture. Levels of satisfaction within physical environment and overall experience varied between posture condition (H(2)=22, p=<0.0001 and H(2)=8.87, p=0.0118 respectively). Figure 20 reveals that all participants expressing dissatisfaction in the physical environment were from the standing posture. Statistically, using Bonferroni correction of 0.0167, participants preferred sitting to standing (Z=-3.69, p=0.0002) and preferred lounging to standing (Z=-4.14, p=<0.0001). Figure 21 reveals different levels of satisfaction with the overall experience by posture condition. Statistically, using Bonferroni correction of 0.0167, sitting respondents preferred the overall experience more than those standing (Z=-2.89, p=0.0039).
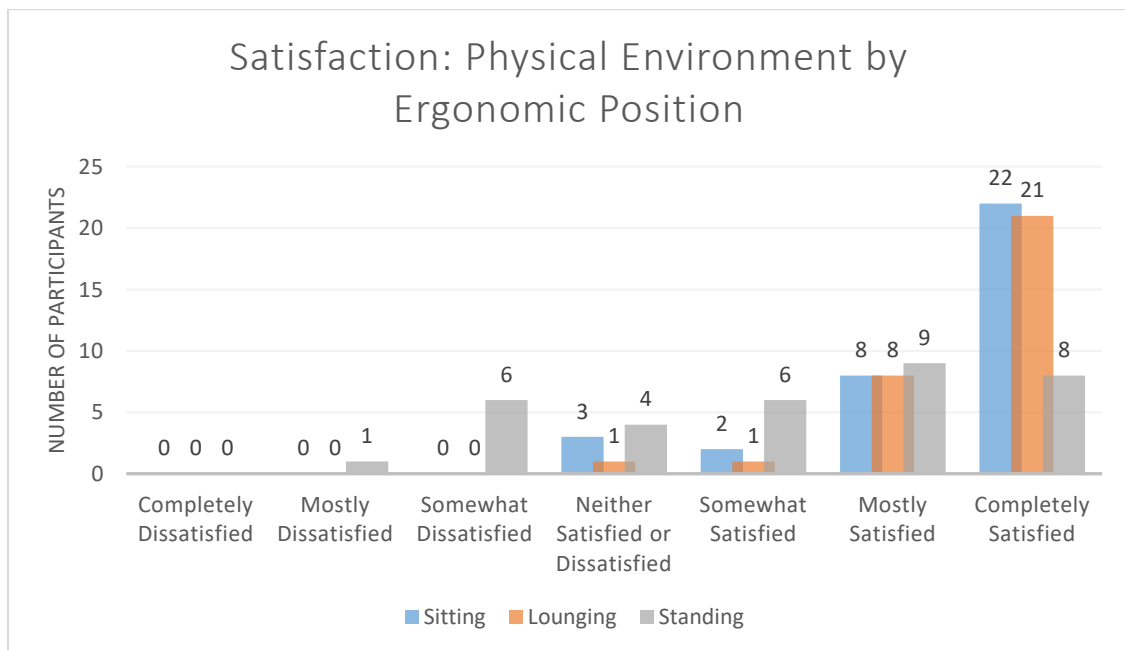

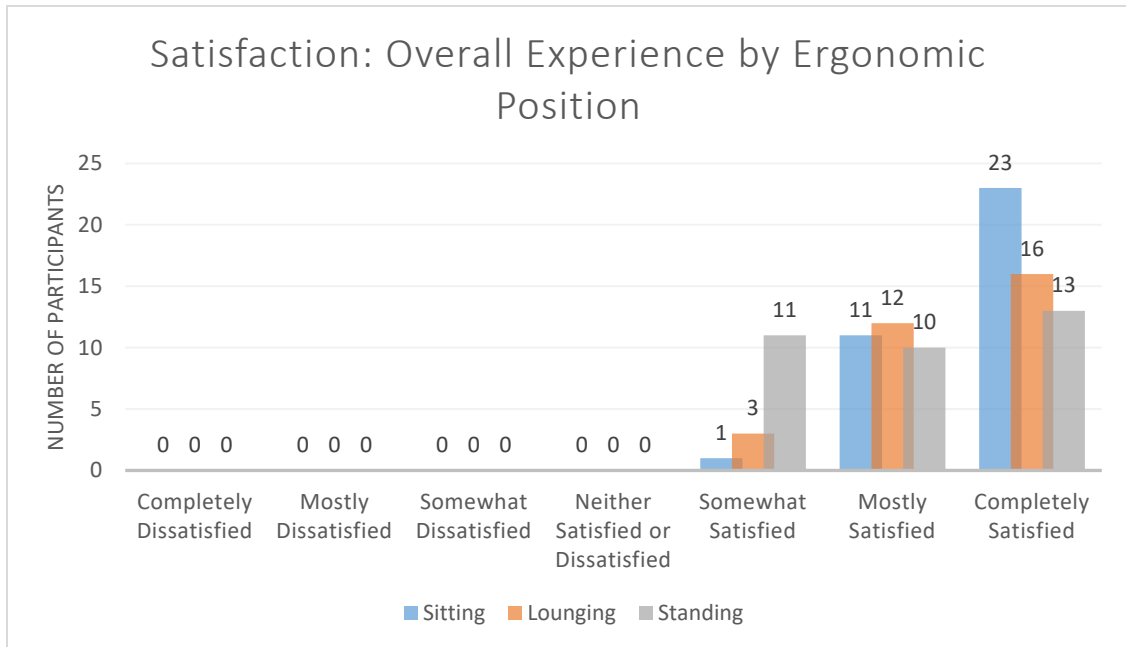Figure 20: Satisfaction: Physical Environment by Location

Figure 21: Satisfaction: Overall Experience by Location

<u>System Observed Data Analysis</u>

Most important to personalized learning is the reliability of sensors to gather data during

game sessions given the above three mITS postures: sitting, standing, and lounging.

Special scripts processed raw data obtained from the tablet sensor inputs and the

Empatica E4 wrist band sensor inputs and fed them into the analytics tool SAS JMP Pro

13. JMP then produced a combined figure consisting of six graphs, for every participant,

as illustrated in Figure 22. These individual participant graphs are all stacked vertically

to associate different metrics (face detection, heart rate, game score, EDA, skin

temperature, and time between gestures) over time.

For clarification, each session is delineated by two vertical lines signaling the start time

and end time of that particular session, practice and trial respectively. The approximately

eight-minute total span of time illustrated in Figure 22 highlights that although total

practice and trial sessions could span fourteen minutes plus the break between sessions,

some individuals finished in less time as no further valid game moves existed.
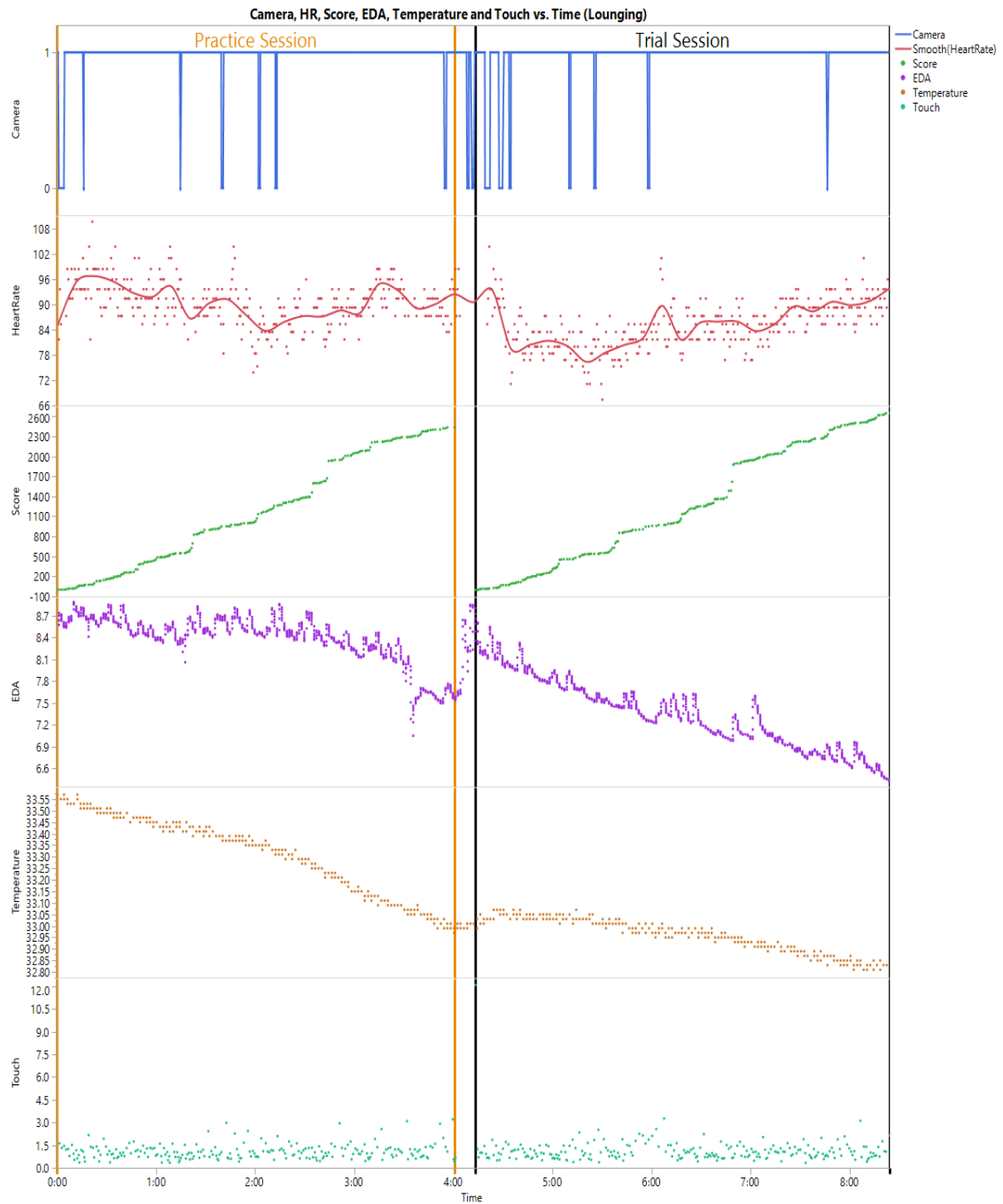
Figure 22: Example aggregate system-observed graphs for a Lounging Participant

The first graph in Figure 22 depicts camera detection of the participant's face with a

value of one indicating the camera found the face and a value of zero represents a missing

face. The second graph indicates the heart rate where JMP Pro fitted a line between

readings. The third graph indicates score within the practice and trials sessions. The

discontinuity in score between the 4:00 and 4:15 time scale depicts the break between

practice and trial sessions. The fourth graph shows EDA obtained by the wrist-worn

monitor. The fifth graph shows the change of skin temperature throughout the sessions

depicted in Celsius. The last graph shows the time of the touch graphed against the

elapsed time since the last touch. For example, approximately at the 4:00 mark, there

was a touch that happened 3 seconds since the last touch.

Camera

Analyzing the camera detection findings, camera detection of the face proved feasible but

overall face detection reliability of 40.6% in practice and 44.9% in trial did not achieve

50% (Table 10). There is statistical evidence that the posture of the participant influences

face detection in both sessions: practice (H(2)=7.21, p=0.0273) and trial (H(2)=13.1,

p=0.0014). Practice session face detection is not statistically different in any of three

postures paired comparisons. In contrast and indicating increased concentration of the

students, the trial session face detection rates finally exceed 50% in sitting and lounging

postures and are statistically different between lounging versus standing (Z=-3.32,

p=0.0009) and sitting versus standing (Z=-2.78, p=0.0054).

Table 10: Percentage of Time Camera Has Detected Face by Session

Camera Detected Face Time / Ergonomic Position	Participants	Average Practice Session Face Detection	Average Trial Session Face Detection	Average Face Detection Difference Between Sessions
Sitting	35	46.9%	51.3%	4.5%
Standing	34	26.3%	27.2%	0.9%
Lounging	31	49.1%	57.1%	7.9%
Overall	100	40.6%	44.9%	4.3%

Table 11 shows the correlation p-values between the rate of the tablet camera's rate of face detection between the two sessions and overall versus the fitted line slope for the touch gesture by ergonomic position. Although there were two slight correlations between the touch gesture rate and face detection for both practice and trial, these correlations (using Spearman's ρ) do not match up for the right period of time (practice versus trial). These correlations are more likely due to random chance since there were 9 different measures by 3 different positions resulting in 27 different combinations.

Table 11: Face Detection and Touch Gesture Correlation by Position

Measure	Face Detection Overall Fitted Line Slope	Face Detection Practice Fitted Line Slope	Face Detection Trial Fitted Line Slope
Gesture Overall Fitted Line Slope	None	None	None
Gesture Practice Fitted Line Slope	None	None	Standing: 0.0299
Gesture Trial Fitted Line Slope	None	Lounging: 0.0327	None

Heart Rate with Wrist Band Monitor

The wrist band heart rate monitor, where the students must place the wrist band on themselves as is the case in unsupervised learning, was feasible but eleven percent of all students did not record wrist-band data: heart rate, EDA, and temperature, as shown in Table 12. Of the remaining 89 students registering heart rates, posture assignment distributions still met Cohen's recommended 26 participants per group size to detect large differences at an alpha of .05 and beta of .2. Fifty-one percent of these had large gaps in heart rate data and could not be used. With the 11% lacking wrist-band data combined with 51% remaining with large gaps in the heart rate data, statistical analysis is unacceptable and raises doubts that personalized learning using an E4 unsupervised wrist band heart rate data is reliable for mITS use.

Table 12: Detailed Missing/Gaps in Heart Rate Data by Ergonomic Position

Ergonomic Position	Participants	Missing HR Data	Large Gaps in HR Data	Gaps in HR Data % (excluding Missing HR Data)
Sitting	35	1	15	44%
Standing	34	5	19	66%
Lounging	31	5	11	42%
Total	100	11	45	51%

EDA

Eleven percent of improperly self-installed wrist band monitors undermines reliability of E4 Empatica EDA readings but the reliability of the remaining participants was statistically sufficient and proved useful. Since the range of EDA values vary greatly from person to person and consistent with the notional of personalized learning, data in Table 13 and subsequent analysis uses normalized EDA values per participant over the span of the experiment. Individually normalized EDA data in Table 13 reveal that standing and lounging participants were under the most stress, followed by the sitting participants. Despite considerable noise, the EDA data appears normally distributed over the practice session (w=0.98, p=0.379), the trial session (w=0.99, p=0.454), and the combined session (w=0.99, p=0.606).

Given unequal sizes, non-parametric analysis indicates ergonomic position influences EDA overall (h=6.34, p=0.042). When considering the sessions separately, ergonomic position did not influence practice session EDA (H(2)=1.68, p=0.4324) but did influence trial session EDA (H(2)=10.4, p=0.0055). Pairwise comparisons indicate trial sitting EDA < trial standing EDA (Z=3.17, p=0.0016). Considering the differences between

practice EDA versus trial EDA, ergonomic position also influenced EDA (H(2)=9.6, p=0.0082), with pairwise comparison indicating the difference between standing and sitting (Z=3.28, p=0.0011) statistically significant.

A line may be fitted to the EDA values. The line slope reveals the direction of stress (i.e. stationary, decreasing, or increasing) corresponding to the direction of the EDA values. An asterisk in Table 13 highlights slopes statistically different from zero with negative slopes indicating reduction in stress for students in the sitting and lounging postures over the practice, trial, and overall. Stress of standing students increased in the practice and overall session. Stress levels due to posture differ for the practice (H(2)=14.9, p=0.0006), trial (H(2)=6.53, p=0.0381), and combined sessions (H(2)=8.8, p=0.0123). The slope for standing differs from sitting for the practice session (Z=3.91, p<0.0001) and combined sessions (Z=2.99, p=0.0028).

Table 13: EDA by Ergonomic Position (Normalized 0 to 1) (* indicates p<.05)

Ergonomic Position	Users	Average Practice EDA	Practice EDA Fitted Line Slope	Average Trial EDA	Trial EDA Fitted Line Slope	Average Overall EDA	Overall EDA Fitted Line Slope	Average Trial-Practice EDA
Sitting	34	.486	-0.0007*	.260	-0.0020	.370	-0.0017*	-0.226
Standing	29	.434	0.0020*	.465	-0.00005	.458	0.0009*	0.030
Lounging	26	.506	-0.0018	.389	-0.0032	.445	-0.0024	-0.118

Table 14 shows the correlation p-values between the slope of the fitted line for EDA

correlated against the touch gesture by session. There is one correlation between touch

gesture practice fitted line slope and EDA trial fitted line slope that doesn't make sense

due to the difference in time (practice versus trial). However, there is a correlation

between overall EDA fitted line slope and overall touch gesture fitted line slope in the

standing ergonomic position. There are a pair of correlations that for touch gesture

during the practice session, against the overall EDA fitted line slope for standing and

lounging. Since the overall session encompasses both practice and trial, this may be a

finding that warrants further investigation in a future study.

Table 14: EDA and Touch Gesture Correlation by Position

Measure	EDA Overall Fitted Line Slope	EDA Practice Fitted Line Slope	EDA Trial Fitted Line Slope
Gesture Overall Fitted Line Slope	Standing: 0.0188	None	None
Gesture Practice Fitted Line Slope	Standing: 0.0385 Lounging: 0.0317	None	Standing: 0.0258
Gesture Trial Fitted Line Slope	None	None	None

Skin Temperature

With respect to the temperature findings, there doesn't appear any discoverable

relationship or statistical evidence. To put the temperature comparisons on equal footing

with all the participants, these readings were normalized between 0 and 1 for the specific

participant's recorded minimum and maximum, as shown in Table 15. Comparisons

between ergonomic position groups proved to be inconclusive (practice: $H(2)=1.47$,

$p=0.4787$; trial: $H(2)=0.63$, $p=0.7286$; combined: $H(2)=1.06$, $p=0.5892$). Using a

regression line technique to determine if the temperature values increase, decrease, or

remain stationary against ergonomic groups also proved to be inconclusive (practice: H(2)=1.05, p=0.5928; trial: H(2)=0.68, p=0.7117; combined: H(2)=0.23, p=0.8928). However, looking at the overall skin temperature difference between the two sessions shows that the median average temperature between practice and trial sessions is less than zero, implying a lower skin temperature in the trial session, regardless of ergonomic position (S=-714, p=0.0015).

Table 15: Average Skin Temperature by Position

Ergonomic Position	Average Practice Temperature	Average Trial Temperature	Average Overall Temperature	Average Session Difference Temperature
Sitting	0.554	0.503	0.551	-0.051
Standing	0.517	0.498	0.549	-0.020
Lounging	0.548	0.478	0.577	-0.700
Overall	0.540	0.494	0.558	-0.046

Score Performance

Student average game scores indicate levels of performance. Table 16 show participants average scores and session time for all participants for both practice and trial. Despite large negative outliers for standing and large positive outliers for lounging, the large standard deviations in game scores contribute to no statistical evidence that practice (H(2)=0.24, p=0.8849), trial (H(2)=1.98, p=0.3719), or difference in score between the two (H(2)=1.03, p=0.5987) is influenced by ergonomic position. Furthermore, there is no statistical evidence that ergonomic position influences time elapsed for the practice (H(2)=0.13, p=0.938), trial (H(2)=2.5, p=0.2863), or difference in time between the two (H(2)=1.21, p=0.545). However, a Wilcoxon-Signed Rank Test for the score differences between practice and trial sessions show that there is statistical evidence that the mean is

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greater than zero (S=1079, p=<.0001), showing overall improvement between the two

sessions.

Table 16: Detailed Score Statistics by Ergonomic Position

Ergonomic Position	Users	Average Practice Score	Average Practice Session Time (s)	Average Trial Score	Average Trial Session Time (s)	Average Score Difference	Standard Deviation Score Difference
Sitting	35	2793.49	328.93	3290.97	336.61	497.49	886.89
Standing	34	2638.59	338.63	2622.47	313.35	-16.12	1705.67
Lounging	31	2931.10	336.40	3690.32	337.60	759.23	1621.06

As discussed earlier, upon a participant move, the game will generate either a 2 or a 4. These game generated tiles will not produce any changes to the participant's score. Therefore, for any given tile, the combined tile score value is composed of game-generated tiles of all 2's, all 4's, or a mixture of the two. Combined tiles composed of game-generated 2's will have a greater value than those combined tiles composed of game-generated 4's due to missing out on the "2+2" combination. Thus, for any given combined tile score, the upper score bound is when comprised of only 2-value tiles, and the lower score bound when comprised of only 4-value tiles. Table 17 highlights the upper and lower bound tile score values and the number of tiles required for tiles 2 through 2048.

Table 17: Upper and Lower Bound Tile Score Values

Tile	Upper Bound Score Value	Upper Bound Tiles Required	Lower Bound Score Value	Lower Bound Tiles Required	Lower Bound Score / Upper Bound Score
2	0	1	N/A	N/A	N/A
4	4	2	0	1	0.00%
8	16	4	8	2	50.00%
16	48	8	32	4	66.67%
32	128	16	96	8	75.00%
64	320	32	256	16	80.00%
128	768	64	640	32	83.33%
256	1792	128	1536	64	85.71%
512	4096	256	3584	128	87.50%
1024	9216	512	8192	256	88.89%
2048	20480	1024	18432	512	90.00%

As evident in Table 17, as the tile number grows, the difference between the upper and lower bound score values continues to narrow. To enumerate other tile scores, the upper and lower bound tile score values can be evaluated using the functions as follows:

$$f_U(t) = t + 2 * f_U\left(t/2\right) \text{ where } f_U(2) = 0 \qquad (1)$$

$$f_L(t) = t + 2 * f_L\left(t/2\right) \text{ where } f_L(4) = 0 \qquad (2)$$

Delay Between Game Moves

Moreover, another component to the participant's score is how much time they took to make their moves, as described in Table 18. When the move times are analyzed against the participant's ergonomic position, there is no statistical evidence that ergonomic position influences average move time for the practice (H(2)=1.13, p=0.5687), trial (H(2)=0.93, p=0.6275), and combined sessions (H(2)=1.51, p=0.4689). However, there

is statistical evidence that everyone achieved faster average move times between the two

sessions (S=-1458, p=<.0001).

Table 18: Detailed Time Between Moves

Ergonomic Position	Users	Average Move Time (s)	Average Practice Move Time (s)	Average Trial Move Time (s)
Sitting	35	1.391	1.478	1.321
Standing	34	1.493	1.550	1.407
Lounging	31	1.407	1.440	1.352

However, when looking at score performance and the time it took the participants to

make moves, an interesting relationship manifests itself as depicted in Figure 23. Due to

the nature of the timed game, the straight forward strategy is to make as many correct

moves in the limited time provided. Thus, the highest scores were from participants that

made the quickest moves that produced points. It stands to reason that for any given

average touch time, there is a ceiling on the maximum score that can be attained since

each session has a maximum of seven minutes. The participants that did not attain the

maximum amount of points with the average touch move time either did not fully

understand the game or have not developed an adequate strategy to obtain points. From

Figure 23, it can also be assumed that a few participants made extremely quick moves

(less than .75 seconds per move on average) and yet received a score less than 3000 were

not participating in earnest.
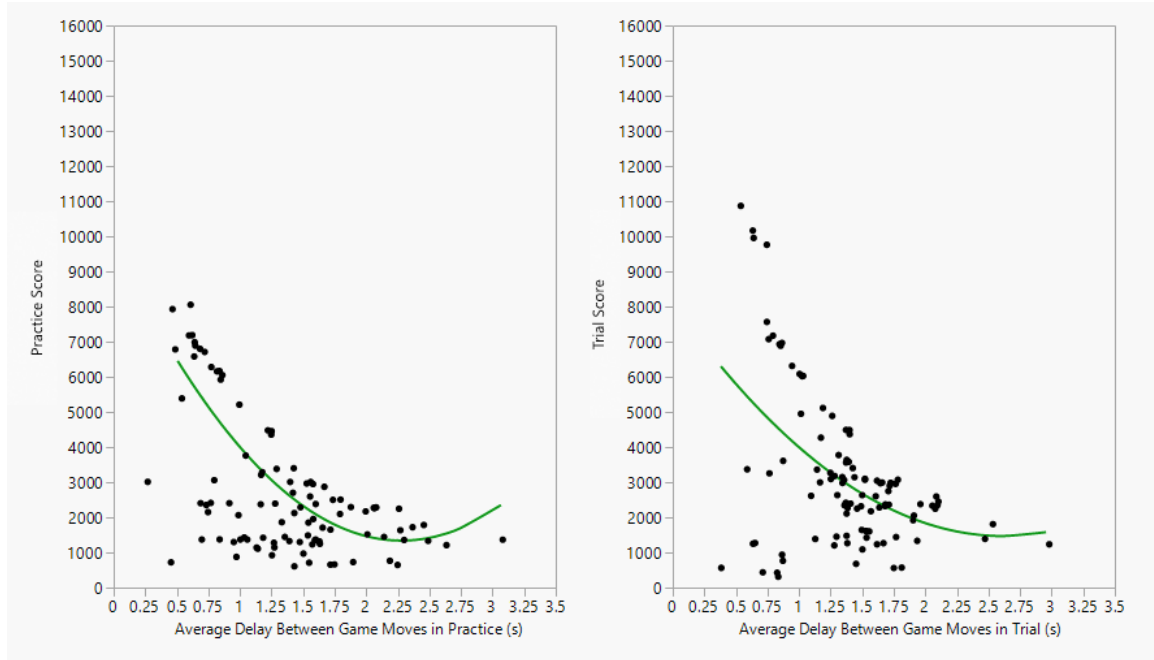
Figure 23: Session Score versus Session Touch Time

When considering the average delay between moves and the score, there must exist an upper-bounded maximum number of moves, assuming that every move generates a combination, which is not the case. In an actual game, the player will receive a mix of generated 2-tiles and 4-tiles, but for the calculation of the upper and lower bounds, let's assume each boundary receives either generated 2-tiles or generated 4-tiles.

Table 19 shows the max number of moves one can make using the average delay between moves within a seven-minute session. Once the maximum number of moves per session has been calculated, then a max score can be calculated. If we assume only 4-tiles are generated by the game, the participant would no longer need to use moves to create combined 4-tiles from generated 2-tiles. Therefore, Table 19 shows the lower-bound for generated 2-tiles and the upper-bound with generated 4-tiles. However, in an actual game, 2048 will generate 2-tiles and 4-tiles, thus, the actual score will fall between these

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two boundaries. From our observed results, nobody had an average delay of more than

3.5 seconds, hence, Table 19 only shows data with a maximum of 3.5 seconds delay

between moves. However, as the delay increases, intuitively, the max number of moves

decreases and the score range also decreases.

Table 19: Analysis of Moves Possible from Delay Between Moves in Seconds per 7-minute Sessions

Delay between moves (s)	Max moves possible per session	Max Score w/generated 2-Tiles per session	Max Score w/generated 4-Tiles per session
0.25	1680	31616	63232
0.5	840	14128	28256
0.75	560	9664	19328
1	420	6224	12448
1.25	336	4992	9984
1.5	280	4272	8544
1.75	240	3008	6016
2	210	2692	5384
2.25	≈186	2292	4584
2.5	168	2160	4320
2.75	≈152	1968	3936
3	140	1856	3712
3.25	≈129	1792	3584
3.5	120	1264	2528

CHAPTER FIVE: SUMMARIZE FINDINGS

The above research seeks to advance personalized learning within unsupervised mITS stand-alone, client-server, cloud and big data applications by establishing initial benchmarks for the feasibility and reliability of basic mobile device sensors to track human physiological signals. Fuad, Deb, Etim, & Gloster (2018), and Shadiev et al. (2018), underscore the emergence of mobile and autonomous educational technology. Use of sensors in desktop ITS (B.-G. Lee & Chung, 2012) and the use of sensors (including use of EDA) in mobile applications (Bahreini, Nadolski, & Westera, 2014; Benta, Cremene, & Vaida, 2015) is not unusual, but the idea of combining them to advance mITS is a novel and emerging idea. Additionally, the research provides a technological approach (mITS2048) and methodology for follow-on research.

Thesis Summary

An Android tablet application, mITS, was initially developed as a prototype or a proof of concept that initially demonstrated how various sensors would interact with the application. The prototype would initialize a connection to a Bluetooth wrist-band device and obtain specific data feeds that was supported by the wrist-band device. Furthermore, mITS would take advantage of innate features of the on-board camera to detect faces and report to the user when the face was lost and log the events internally. Although not used in the study described in Chapter 4, the prototype also communicated with the GIFT framework to provide course material.

Modifying the mITS prototype by incorporating the game 2048 lead to the development of mITS2048. The new application, mITS2048, allowed mobile sensor data to be gathered for later analysis while the participants played 2048 after they were assigned to one of three ergonomic positions: sitting, lounging, and standing. The study was driven by the idea of taking advantage of sensors already attached to the learning mobile device, along with any accessories that can also interact with the device. These sensors produced data which can be used to empirically evaluate the effectiveness of these sensors. Using these findings would allow the software to better predict the state of the user and personalize their learning accordingly.

The 100 participants were obtained from the pool of students in the UCF Psychology SONA system that offers the students extra credit in their psychology courses in exchange to participate in real-world studies giving them first-hand experience. Since General Psychology is one of the course choices within the "Social Foundation" of the required UCF General Education Program (UCF, 2018), a variety of majors elect to take this course providing a representative sample of the UCF undergraduate population. This exchange benefits researchers since they can take advantage of a large pool of willing UCF undergraduate participants. As described in Table 6, 82% of the participants were 18 years old, 11% were 19, 3% were 20, and 4% were 21 or older, leading to the assumption that the bulk of the participants were fulfilling the UCF General Education Program. Furthermore, Figure 17 shows the participant's study discipline (or major) is varied.

Participants reserved an available timeslot within the UCF Psychology SONA system and arrived at the agreed upon location. They were randomly assigned to one of three locations: desk (sitting), sofa (lounging), or behind a podium (standing). They were outfitted with the Empatica E4 wristband on their dominant hand and the external camera was positioned and started. Each participant filled out the demographic survey and reported their mood before they started the practice session. After the practice session, they were notified that the trial session would begin upon their button push. At the conclusion of the trial session, they were to fill out the satisfaction survey and report their mood one last time. Finally, the external camera was turned off and the Empatica E4 wrist-band was removed and turned off.

The findings of the study, that support or reject the research questions identified in the third chapter, can be summarized within Table 20.

Table 20: Research Question, Data, and Analysis Summary

Abbreviated Research Question & Null	Statistical Inference	Response Level	Reference
1. Does the tablet's camera provide an effective mechanism to track eye gaze for a given ergonomic setting? **H₀:** N/A, Descriptive Statistics Utilized for Analysis	N/A	Overall 40.6% detection in practice and 44.9% in trial sessions, but over 50% camera detection while sitting and lounging during the trial session.	Table 10
2. Does the tablet's camera provide an effective mechanism to track facial expression for a given ergonomic setting? **H₀:** N/A, Descriptive Statistics Utilized for Analysis	N/A	Tablet camera software tracks eyes and faces, but API limitations does not track facial expression.	N/A
3. Does the ergonomic position of the user impact the effectiveness of the tablet camera's face detection? **H₀:** The tablet camera's face detection capability is equally effective in all selected ergonomic settings.	Reject Null	Although neither ergonomic position approach 60%, both sitting and lounging fare better than standing.	Table 10
4. Is face detection rate correlated with touch gesture frequency rate by different ergonomic positions? **H₀:** The tablet camera's face detection rate and touch gesture frequency rate are equivalent for each ergonomic position.	Reject Null	There is no significant correlation between face detection rate and touch gesture frequency rate by ergonomic positions.	Table 11
5. Does the wrist monitor provide an effective mechanism to track heart rate activity when paired with a tablet? **H₀:** N/A, Descriptive Statistics Utilized for Analysis	N/A	No, 11% completely missing heart rate data, and 51% remaining had large gaps in heart rate data.	Table 12

Abbreviated Research Question & Null	Statistical Inference	Response Level	Reference
6. Does the wrist monitor provide an effective mechanism to track electrodermal activity when paired with a tablet? **H_0:** N/A, Descriptive Statistics Utilized for Analysis	N/A	100% of the participants that had properly worn wrist-band produced usable EDA data.	Table 13
7. Does the wrist monitor provide an effective mechanism to track skin temperature when paired with a tablet? **H_0:** N/A, Descriptive Statistics Utilized for Analysis	N/A	100% of the participants that had properly worn wrist-band produced usable skin temperature data.	Table 15
8: Does the user's ergonomic position impact the electrodermal activity captured by the wristband? **H_0:** The electrodermal activity captured by the wristband is equivalent for each ergonomic position.	Reject Null	There is a statistical difference in ergonomic positions for average practice, trial, and overall EDA.	Table 13
9: Is electrodermal activity captured by the wristband correlated with touch gesture frequency rate by different ergonomic positions? **H_0:** The electrodermal activity captured by the wristband is correlated with touch gesture frequency rate for each ergonomic position.	Reject Null	There appears to be a correlation between EDA and touch gestures in the standing ergonomic position, but not for the other positions.	Table 14
10: What is the relationship between the game score performance and the ergonomic position of the user? **H_0:** The game score performance by ergonomic position of the user is equivalent.	Fail to Reject Null	There is no statistical evidence that ergonomic position affects game score performance for any of the sessions.	Table 16, Figure 23
11: What is the relationship between the delay between game moves and the ergonomic position of the user? **H_0:** The delay between game moves and the ergonomic position of the user is equivalent.	Fail to Reject Null	There is no statistical evidence that the ergonomic position affects the delay between game moves for any of the sessions.	Table 18, Figure 23

Findings and Conclusions

Survey Findings

Statistical analysis of the three different postures groups did not indicate any difference in demographics, level of technology or game genre familiarization, or level of game enjoyment. Additionally, pre and post experiment component user affect and satisfaction levels point to greater levels of sadness and dissatisfaction with the standing posture than either sitting or lounging. That infers that students utilizing a mITS may assume a standing posture but that posture will likely evolve into either a lounging or sitting posture for the purposes of studying with an intelligent tutoring system.

Camera Findings

With respect to sensors, the standard camera tracks the student face at over 50% reliability in the two preferred postures, sitting or lounging, when concentrating on a task and aided by the student being alerted by the large red border indicating a lost detected face. Camera tracking of the face for standing students never achieves 50% reliability in our experiment. One may speculate that students lost interest and looked away from the tablet, but external camera footage does not support inferred disinterest. Rather external camera footage of student facial orientation is toward the tablet. In a camera detection lecturer/student study (Thepsoonthorn et al., 2015) the average percentage of time a camera detected that both parties were facing each other was 52.83%, which is similar to the results we observed. In Thepsoonthorn's study (2015), it was hypothesized the low rate of mutual gaze detection was due to alternating attention spans of the students, and the lecturer recalling information disrupting mutual gazes. Another example is the effort

on the CarSafe Android app, which takes into consideration the mobile nature of the technology, reports the detection of face and eyes for drowsy driving at only 60% (You et al., 2013).

Although the FOV specification was not available by the manufacturer, experimental tests estimate that when held in a portrait orientation, the Nexus 7 (2013) has a horizontal FOV of 40 degrees and a vertical field of view of 60 degrees. The Nexus 7 (2013) can only capture a small fraction of the environment when compared to newer mobile devices that come equipped with camera technology that can comfortably obtain field of views at least between 80 and 120 degrees ("LG V10 vs Galaxy Note 5 vs Nexus 6P Camera Comparison," 2015). Realistically, increasing camera field of view would be performed by upgrading the tablet hardware which includes a feature-rich front facing camera technology. External camera footage of student facial orientation during the experiment is consistently toward the tablet indicating the student's intense interest in the experiment. Camera detection of the face proved feasible but the likely wobble of the tablet and occasional movement of the student's body out of the camera's field of view (FOV) is the most probable cause of the overall camera detection of 40.6% in practice and 44.9% during the trial as shown in Table 10.

Wrist-band Findings

The Empatica E4 wrist band monitor provides EDA, skin temperature, and heart rate and accelerometer data (Empatica, 2016). Under the assumption of unsupervised use of wrist band monitor in a mITS application, approximately 10% of the cases either improperly installed the wrist band or the monitor did not operate properly. Similar findings have

been observed in different studies attributed to participants not following directions (14-28%) (Oppenheimer, Meyvis, & Davidenko, 2009), improper use or technical errors of the wrist-band (~20%) (Kinnunen, Tanskanen, Kyröläinen, & Westerterp, 2012; van Hees et al., 2011) For the remaining properly installed bands, our observed unreliability of heart rate data appears to support the literature. Parak and Korhonen (2014) indicate the pulse photopletysmography (PPG) can estimate heart rate between 76 and 78%, with different activities producing a different level of estimation. Additionally, Spierer, Rosen, Litman, and Fujii (2015) questions the effectiveness of PPG heart rate monitors when dealing with different skin types. From this study, student installed wrist-band heart rate data is inconsistent due to technical factors.

While EDA and skin temperature data collection suffered from the same approximately 10% improperly installed or working bands, the remaining EDA and skin temperature data proved reliable. When EDA data is normalized to an individual, relative values appear to identify levels of stress as well as whether stress is increasing, decreasing, or staying the same. Anusha, Joy, Preejith, Joseph, & Sivaprakasam, (2017); Quick et al. (2017); and Sarchiapone et al., (2018) all had similar findings. Of the three wrist-band statistics, heart rate, EDA, and skin temperature, EDA data proved to be the most meaningful in terms of human physiology during the experiment. From the EDA data, participants exhibited more stress when standing versus those that were standing.

Skin temperature data did not reveal any insights other than the participant's temperature cooled throughout the study. This could be from the result of many factors such as: colder classroom temperature compared to outside environment temperature, less stress

driving skin temperature lower, or even a raised cardiovascular level from trying to arrive to the study on time.

<div align="center">*Score and Touch Gesture Findings*</div>

Focusing on the delay between gestures and a participant's highest score, there are multiple variables that are factored into the outcomes of the participant's performance. From the analysis in Table 19, there is a theoretical maximum number of moves within the timed session, which produces a range depending on which tiles are generated by the game. The score range grows as the number of moves are maximized when the delay between gestures is minimized. While also minimizing the delay between gestures, maximizing the score is dependent on making the correct move that generates the best probability for a higher score in the long-term. Figure 23 shows a number of participants that were able to increase their maximum score by also decreasing their average delay between game moves. The green fitted curve shows that the average participant game score in the trial session stays higher than those from the practice session. There is statistical evidence that the participants improved in the trial session, regardless of ergonomic position.

The probabilistic nature of the game may result in slight variations of high scores between players with the exact level of proficiency. However, just like in similar games of chance, such as online poker where skill dominates chance in the long-term (van Loon, van den Assem, & van Dolder, 2015), similar results should be present in the 2048 game.

Research Limitations

During the development of the mITS prototype and proposal, the research moved forward under the clear assumption and limitation that it was going to narrow the focus of the research, and inherently lock down the hardware to the items accessible to the study. In other words, developing the prototype lead the study into using the Nexus 7 with Qualcomm chipset that powers the front-facing camera and a heart-rate monitor that communicates with Bluetooth LE as the primary vehicle for its mobile sensors.

It would have taken an extra effort to convert the mITS prototype to use another proprietary camera API associated with another tablet in order to modernize the equipment used in the study. Therefore, the study was limited by the hardware used before the proposal phase.

It was also proposed that limiting the scope of the study to focus on the mobile sensor would keep the study manageable. The development of a suitable and validated course within an ITS Framework, such as GIFT would have added an extra layer of complexity, which would include the configuration of a server to manage the course data for all the participants. Furthermore, the server would need to consider appropriate levels of security in order to protect the personally identifiable information from the participants, and make sure the UCF Wi-Fi maintains connectivity to the cloud-hosted ITS.

Lessons Learned

Although the study produced findings that can be used in future studies, it has also revealed lessons learned which could have been applied to this study. If we were to

increase the number of participants available to the study, it is important to have more equipment. By having only one complete set of equipment, the number of willing participants exceeded the number of timeslots they could reserve. Even if the study design allowed at most one participant at a time in a particular randomized posture, oftentimes there is a downtime between the time when there were active participants in the study, and thus, the efficiency could have been better maximized. Having a backup set of study equipment would've allowed for more slots even accounting for the worst case of the same posture location for the allotted reserved time.

Whenever the participants arrived to the study location, an interesting observation was revealed when they arrived in varying levels of physical cardiovascular stress levels. For example, some individuals had to run others even biked across campus in order to arrive on time. Although the few minutes of setup before they can actually participate may have lessened this factor and allowed a rest period, increasing the setup time before the participation may help ensure physiological data starts at a baseline.

With respect to mITS2048, at times, the participants had some questions with the survey, and with some of the screen flow. If I were to perform the study again, I would incorporate some more tooltips and on-screen instructions to minimize the number of questions asked to the researcher. This would increase the amount of independence the participants had in the study.

Another lesson learned during the study is how much the participants enjoyed the experience. Although evident from Figure 20 and Figure 21, parting verbal discussions

with numerous participants expressed that did not enjoy other Psychology SONA studies as much as they enjoyed interacting with mITS2048 and were surprised to find a study they enjoyed.

Suggested Future Research

The promise of expanding Intelligent Tutoring Systems into the mobile space is an endeavor worth investigating. Limitations to our research point to possible areas of future research using the methodologies, GIFT ITS framework, and mITS2048 we demonstrated above. For future researchers, our sample sizes only enabled identification of large differences in sensor feasibility and reliability on an Android tablet for personalizing learning using a standard front-facing camera with an E4 wrist band. Future research using large sample sizes may enable identification of medium and small differences. Future research using tablets with cameras with larger fields of view may determine if increase field of view increases camera detection of the face. In order to rule out the possibility that the quality of lighting is inappropriate in the study location, the ambient light sensor available in mobile devices can help the application better react to possible poor camera detection due to bad environment lighting.

With the study rating positively by the participants, one can hypothesize if the results would be the same if they were forced to play more sessions, longer sessions, or a combination of the two. Future research could explore this possibility, and it would be one assumption that Figure 20 and Figure 21 would show even more disparity. Furthermore, another consideration would be to change the study design to have all

participants try multiple postures and compare the different ergonomic metrics per individual.

Although we did not consider smartphones as part of this study, it would be trivial to adapt most of the mITS2048 software to run on an Android smartphone. Ergonomically, smartphones are gripped differently than tablets by users, hence are likely to have different levels of feasibility and reliability (Trudeau, Catalano, Jindrich, & Dennerlein, 2013). Another consideration for this study was the use of the Empatica E4 wrist band, but other wrist bands may be investigated, such as the Mio Slice and Biostrap just to name a few. For future research, even more modern human physiological monitors exist that are embedded into the tablet itself and do not require the user to attached a wrist band, such as using the built-in camera to detect heart rate (Han, Xiao, Shi, Canny, & Wang, 2015; Poh, McDuff, & Picard, 2010). Finally, while this research considers passive sensors, future research may consider active conversational intelligent tutors on mITS devices that detect human affect levels based on inflections in student voice patterns (Bahreini et al., 2014; Hart & Proctor, 2018).

When considering the design of an ITS that would ultimately interact with mITS2048, one possible strategy for personalizing the participant's learning is to use the current score with the current delay between touches. If the participant is not falling within the range of the theoretical maximum as identified in Table 17 and Table 19, hints or tooltips can be displayed to the user in order to provide some level of assistance. Inspecting Figure 23 shows that participants that are not at the maximum within that specific time delay can be encouraged to improve. Once the participant is at the maximum for that

specific time delay, the ITS can start to encourage them to start decreasing their delay

between gestures, in order to take advantage of more moves and thus, increasing their

score performance. In other words, if the region of the best score is plotted against the

delay between moves, the system should get the participant to move within the region

while increasing their speed.

Any future research should include an increased number of participants to include a

desktop-based group that does not use a tablet. The game (or ITS course) should be

ported to run on a desktop environment for future comparison to the mobile positions.

APPENDIX A: AFFECTIVE SLIDER
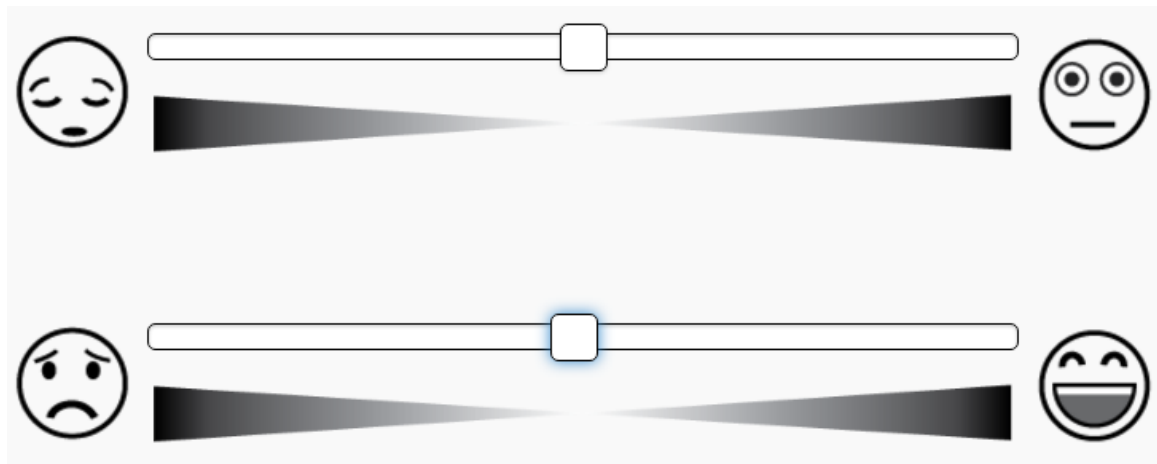
Figure 24: Affective Slider (Betella & Verschure, 2016)

As already discussed in the fourth chapter, the Affective Slider is licensed under the

Creative Commons license CC BY-SA 4.0. The license requires us to provide attribution

(done by citation) and a link to the license (Creative Commons, 2018). The images were

not changed when included in mITS2048, therefore the ShareAlike clause of the license

would not apply to this study.

APPENDIX B: DEMOGRAPHIC QUESTIONNAIRE

Figure 25: Demographic Questionnaire

APPENDIX C: USER SATISFACTION SURVEY

Figure 26: User Satisfaction Survey

APPENDIX D: IRB APPROVAL LETTER

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Human Research

From: **UCF Institutional Review Board #1**
          FWA00000351, IRB00001138

To: **Luis Vazquez** and Co-PI: **Michael D. Proctor**

Date: **April 21, 2017**

Dear Researcher:

On 04/21/2017 the IRB approved the following modifications to human participant research until 04/11/2018 inclusive:

Type of Review:	IRB Addendum and Modification Request Form Expedited Review
Modification Type:	Addition of Florian Jentsch, addition of recruitment from IST SONA
Project Title:	Exploring the potential of sensors to enhance tablet-based Intelligent Tutoring Systems
Investigator:	Luis Vazquez
IRB Number:	SBE-17-12944
Funding Agency:	
Grant Title:	
Research ID:	N/A

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at https://iris.research.ucf.edu .

If continuing review approval is not granted before the expiration date of 04/11/2018, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

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On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Gillian Amy Mary Morien on 04/21/2017 03:59:24 PM EDT

IRB Coordinator

APPENDIX E: JMP JSL SCRIPT TO GENERATE PARTICIPANT GRAPHS

JMP JSL Script to generate participant graphs.

```
directory = get default directory();

fileNames = Files In Directory( directory );

For( iFile = 1, iFile <= N Items( fileNames ), iFile++,
  GSRNotFound = 1;
  filename = fileNames[iFile];
  If( Ends With( filename, "combined.csv" ),
        dt = Open( directory || filename );

        col_name_list = dt << get column names(string);

        if (!(contains(col_name_list, "Camera")>0),
      dt <<New Column("Camera", Numeric, "Continuous", 0)
        );

        if (!(contains(col_name_list, "HeartRate")>0),
      dt <<New Column("HeartRate")
        );

        if (!(contains(col_name_list, "GSR")>0),
      dt <<New Column("GSR"), GSRNotFound = 0
        );

        if (!(contains(col_name_list, "Temperature")>0),
      dt <<New Column("Temperature")
        );

        if (!(contains(col_name_list, "Score")>0),
      dt <<New Column("Score")
        );

        valuesList = :StudyLocation_Name <<
        Get Values(
        );

        location = Empty();

        For ( iValue = 1, iValue <= N Items (valuesList), iValue++,
              If(valuesList[iValue] != "", location = valuesList[iValue]; Break() );
        );
```

```
// Calculate offset time
// Code to find OffsetStart
x = col minimum(:"Restart Game_Practice");
rmat = dt << get rows where(:"Restart Game_Practice" == x);
r = rmat[1];
offsetTimeStart = :Time[r];
offsetTime = dt:Time << getValues;

For (index = 1, index <= N items(offsetTime), index++,
        offsetTime[index] = offsetTime[index]-offsetTimeStart;
);

dt:Time << setValues(offsetTime);

PSs = 0;
PSe = 0;
TSs = 0;
TSe = 0;

// Code to find PSs
x = col minimum(:"Restart Game_Practice");
rmat = dt << get rows where(:"Restart Game_Practice" == x);
r = rmat[1];
PSs = :Time[r];

// Code to find PSe
x = col minimum(:"Game Ended_Practice");
rmat = dt << get rows where(:"Game Ended_Practice" == x);
r = rmat[1];
PSe = :Time[r];

// Code to find TSs
x = col minimum(:"Restart Game_Trial");
rmat = dt << get rows where(:"Restart Game_Trial" == x);
r = rmat[1];
TSs = :Time[r];

// Code to find TSe
x = col minimum(:"Game Ended_Trial");
rmat = dt << get rows where(:"Game Ended_Trial" == x);
r = rmat[1];
TSe = :Time[r];

// Rename GSR to EDA
columnReferenceList  = dt << get column reference();
```

```
position = contains(columnReferenceList, column("GSR"));
column(position)<<setName("EDA");

gb = dt<<Graph Builder(
        Size( 1065, 1240 ),
        Show Control Panel(0),
        Variables(
                X( :Time ),
                Y( :Camera ),
                Y( :HeartRate ),
                Y( :Score ),
                Y( :EDA ),
                Y( :Temperature ),
                Y( :Touch)
        ),
        Elements(
                Position( 1, 1 ),
                Points( X, Y, Legend( 30 ) ),
                Line( X, Y, Legend( 32 ) )
        ),
        Elements(
                Position( 1, 2 ),
                Points( X, Y, Legend( 28 ) ),
                Smoother( X, Y, Legend( 29 ), Lambda( 0.00001 ) )
        ),
        Elements( Position( 1, 3 ), Points( X, Y, Legend( 10 ) ) ),
        Elements( Position( 1, 4 ), Points( X, Y, Legend( 4 ) ) ),
        Elements( Position( 1, 5 ), Points( X, Y, Legend( 21 ) ) ),
        Elements(
                Position( 1, 6 ),
                Points( X, Y, Legend( 33 ) )
        ),
        SendToReport(
                Dispatch( {}, "Graph Builder",
                        OutlineBox, {Set Title( "")}
                ),
                Dispatch(
                        {},
                        "Time",
                        ScaleBox,
                        {Format( "min:s", 11, 0 ), Min( 0 ), Max( TSe ), Interval( "Minute" ), Inc( 1 ),
                        Minor Ticks( 0 ), Label Row(Label Orientation( "Horizontal" )),
                        Add Ref Line( PSs, "Solid", {230,138,0}, "", 3 ),
                        Add Ref Line( PSe, "Solid", {230,138,0}, "", 3 ),
                        Add Ref Line( TSs, "Solid", "Black", "", 3 ),
                        Add Ref Line( TSe, "Solid", "Black", "", 3 )}
```

```
            ),
            Dispatch(
                    {},
                    "Camera",
                    ScaleBox,
                    {Format( "Fixed Dec", 12, 0 ), Min( -0.2 ), Max( 1.2 ), Inc( 1 ),
                    Minor Ticks( 0 )}
            ),
            Dispatch(
                    {},
                    "graph title",
                    TextEditBox,
                    {Set Text( "Camera, HR, Score, EDA, Temperature and Touch vs. Time (" || location || ")" )}
            ),
            Dispatch(
                    {},
                    "Graph Builder",
                    FrameBox,
                    {Marker Size( 1 ), Add Graphics Script(
                            3,
                            Description( "Script" ),
                            Text Size (16);
                            Text Color ({230,138,0});
                            Text(
                                    {PSs, 1.20, PSe, 1.05},
                                    "Practice Session"
                            );
                            Text Color ("black");
                            Text( {TSs, 1.20, TSe, 1.05}, "Trial Session" );
                    )}
            ),
            Dispatch( {}, "Graph Builder", FrameBox( 2 ), {Marker Size( 1 )} ),
            Dispatch( {}, "Graph Builder", FrameBox( 3 ), {Marker Size( 1 )} ),
            Dispatch( {}, "Graph Builder", FrameBox( 4 ), {Marker Size( 1 )} ),
            Dispatch( {}, "Graph Builder", FrameBox( 5 ), {Marker Size( 1 )} ),
            Dispatch( {}, "Graph Builder", FrameBox( 6 ), {Marker Size( 1 )} ),
            Dispatch( {}, "Y 3 title", TextEditBox, {Rotate Text( "Left" )} )

        )
    );

    gb << Save Picture( directory || "graphs/" || filename || "." || location || ".png", "png");

    gb << Save Picture( directory || "graphs/" || location || "/" || filename || "." || location || ".png", "png");

Close( dt, "nosave" );
```

```
        Show(iFile);
        Show(filename );
    );
);
```

APPENDIX F: MITS PROTOTYPE EVOLUTION
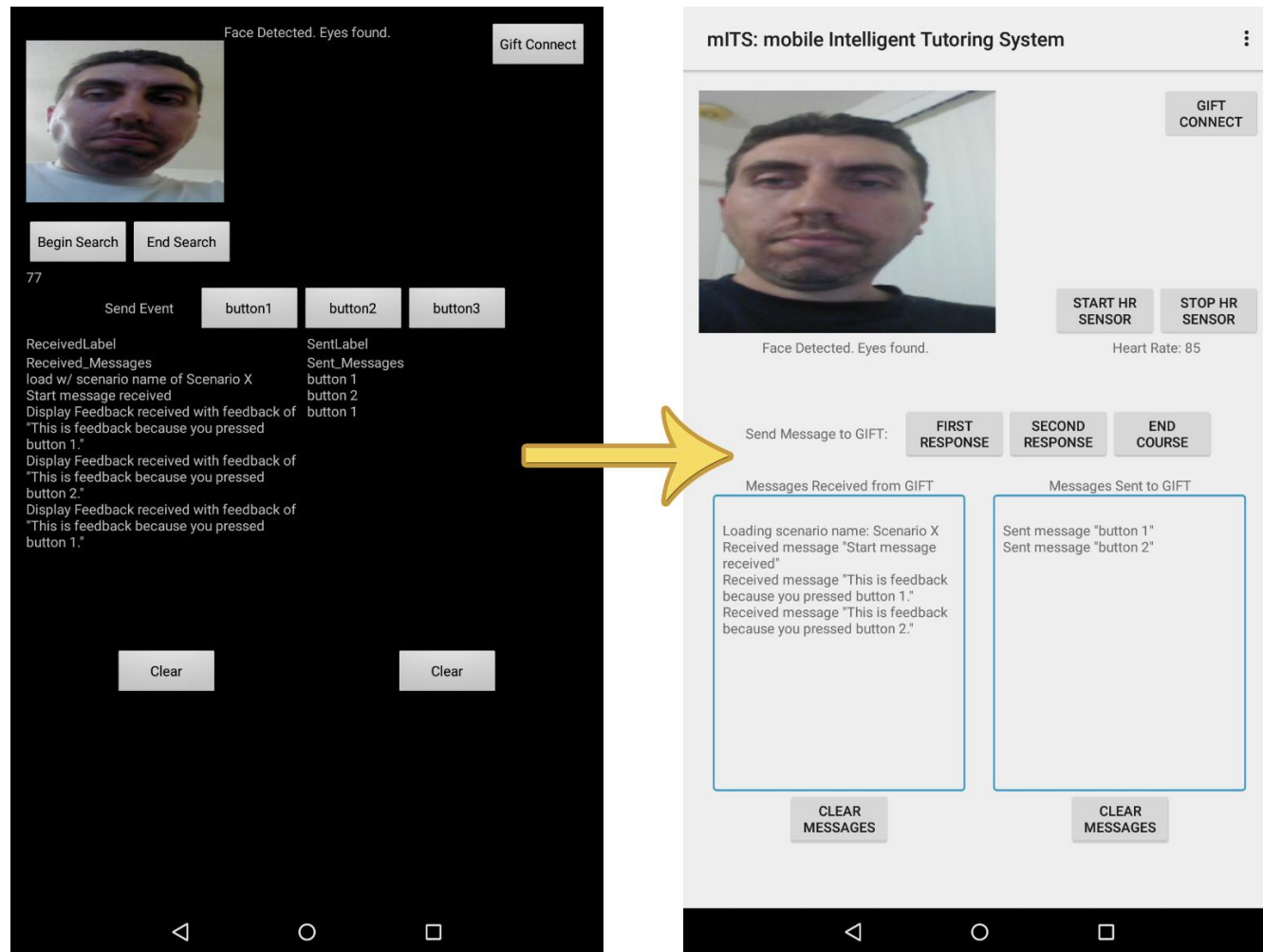
Figure 27: Early mITS Prototype Evolved to Final

Figure 28: mITS to mITS2048 Evolution

Figure 29: mITS Participant Log Structure

APPENDIX G: SYSTEM-OBSERVED PARTICIPANT DATA

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Practice Session

Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Practice Session

Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

151

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Practice Session

Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

156

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Practice Session

Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Practice Session

Trial Session

Camera
Smooth(HeartRate)
Score
EDA
Temperature
Touch

Time

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Practice Session

Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Practice Session

Trial Session

179

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

181

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Practice Session

Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Practice Session

Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Practice Session

Trial Session

195

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

209

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Practice Session

Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Lounging)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Practice Session   Trial Session

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Standing)

Camera, HR, Score, EDA, Temperature and Touch vs. Time (Sitting)

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