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Individual-Technology Fit: Matching Individual Characteristics and Features of Biometric Interface Technologies with Performance

Adriane Randolph

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INDIVIDUAL-TECHNOLOGY FIT: MATCHING INDIVIDUAL CHARACTERISTICS AND FEATURES OF BIOMETRIC INTERFACE TECHNOLOGIES WITH PERFORMANCE

BY

ADRIANE B. RANDOLPH

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree
of
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in the Robinson College of Business
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Acceptance

This dissertation was prepared under the direction of Adriane B. Randolph's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Robinson College of Business of Georgia State University.

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Abstract

INDIVIDUAL-TECHNOLOGY FIT: MATCHING INDIVIDUAL CHARACTERISTICS AND FEATURES OF BIOMETRIC INTERFACE TECHNOLOGIES WITH PERFORMANCE

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The term *biometric* literally means "to measure the body", and has recently been associated with physiological measures commonly used for personal verification and security applications. In this work, biometric describes physiological measures that may be used for non-muscularly controlled computer applications, such as brain-computer interfaces. Biometric interface technology is generally targeted for users with severe motor disabilities which may last long-term due to illness or injury or short-term due to temporary environmental conditions. Performance with a biometric interface can vary widely across users depending upon many factors ranging from health to experience. Unfortunately, there is no systematic method for pairing users with biometric interface technologies to achieve the best performance. The current methods to accommodate users through trial-and-error result in the loss of valuable time and resources as users sometimes have diminishing abilities or suffer from terminal illnesses. This dissertation presents a framework and methodology that links user characteristics and features of biometric interface technologies with performance, thus expediting the technology-fit process. The contributions include an outline of the underlying components of capturing and representing individual user characteristics and the impact on the performance of basic interaction tasks using a methodology called *biometric user profiling*. In addition, this work describes a methodology for objectively measuring an individual's ability to control a specific biometric interface technology such as one based on measures of galvanic skin response or neural activity. Finally, this work incorporates these concepts into a new individual-technology fit framework for biometric interface technologies stemming from literature on task-technology fit.

Key words: user profiles, biometric user profiling, biometric interfaces, fit, individual-technology fit, galvanic skin response, functional near-infrared, brain-computer interface

1. Introduction

Researchers in the field of management information systems (MIS) explore the impact of technology on various types of organizations ranging from businesses to homes. Spanning MIS and computer science, the field of human-computer interaction (HCI) "lies at the intersection between the social and behavioral sciences… and computer and information technology…" (Carroll, 2003). Its focus is to study ways of making devices and computer systems more usable for people through advances in design. One way design has allowed systems to become more usable is by adjusting to fit the needs of specific individuals, such as through assistive technology. Assistive technology augments the functional capabilities of people with disabilities. Traditional computer applications and assistive technology devices require muscle movement for input, such as needed to manipulate a mouse and keyboard or a sip-and-puff switch.

The term *biometric* literally means "to measure the body", and has recently been associated with physiological measures commonly used for personal verification and security applications. In this work, biometric describes physiological measures that may be used for non-muscularly controlled computer applications, such as brain-computer interfaces, (Mason, Moore Jackson, & Birch, 2005; Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002) and can therefore be considered assistive technology. Biometric interface technology has been demonstrated in assistive technologies generally targeting users with severe motor disabilities as a result of disease, illness, or injury and able-bodied users with physical disabilities temporarily induced by their environment, such as with jet pilots subjected to extreme forces or soldiers in hostile territory. Biometric interfaces provide these users with capabilities for communication and control of environmental, navigational, and prosthetic devices. As a result, people who might not otherwise have an outlet can interact with their friends and family members and take more proactive roles in their environment. Thus, severely disabled users who are able to control biometric interface technologies can experience a significant improvement in their quality of life (Moore, 2003). However, everyone does not experience equal success with controlling this technology; where someone is able to control a particular biometric interface technology with great reliability, another cannot control it at all. The match between an individual and technology is their *individual-technology fit* and can be reflected by the individual's performance with the technology.

More people would be able to effectively utilize biometric interface technologies if we understood more about the factors that affect performance with these systems. Currently, there exists a disparity in goals among researchers and assistive technology practitioners investigating biometric interfaces. Researchers tend to focus more on characteristics of the technology being developed and practitioners focus more on characteristics of the user. The result is that available biometric interface technologies are often matched to users through trial-and-error based on the specialized knowledge of the attending team. Unfortunately this unsystematic approach can waste valuable time and resources as users sometimes have diminishing abilities or suffer from terminal illnesses which preclude them from enjoying the full benefits of the provided system. A methodology that explains performance with available biometric interface technologies based on individual characteristics can greatly expedite the technology-fit process.

This work examines an important consideration for biometric interface design: describing characteristics of an individual user and his or her fit with a specific technology. *Characteristics* are a person's demographic, physiological, and cognitive traits. Individuals vary in their characteristics across many dimensions. It is necessary to develop paradigms and heuristics that link individual characteristics to available technologies to determine which approach is likely to be most effective. Then, assistive technology practitioners may better incorporate information about their users to refine their design efforts, and research teams may refer these users to other targeted groups specializing in the most appropriate technology. With better means for explaining performance with various biometric interface technologies, we make better use of the time and resources expended in offering impactful solutions to a sensitive user population. Further, we help advance the field of biometric interface technology for mainstream use by able-bodied persons by understanding the overall concept of individual-technology fit.

There are models and processes in existence for matching people with various technologies but these models have not yet been applied to the more non-traditional technology associated with biometric interfaces. In addition, these models are not intended to uncover the salient user characteristics necessary for an effective pairing with various biometric interface technologies. Therefore, this research proposes that: *salient individual user characteristics may be identified and modeled in a way that matches with features of biometric interface technologies to explain performance*. Specifically this research seeks to answer the following questions:

RQ1: ***What are the salient characteristics of users to inform biometric interface design, and to what extent can they be modeled?***

RQ2: ***To what extent can performance with a biometric interface technology with a specific user be objectively measured?***

RQ3: ***To what extent can individual characteristics of users match with technology features to explain performance with biometric interfaces?***

The following sections of this manuscript describe a new individual-technology fit framework that explains performance with biometric interface technologies based on individual characteristics. First, the manuscript provides background on biometric interfaces, assistive technologies, existing techniques for capturing information about users for system personalization and performance enhancement, and theory describing technology-fit. Second, the manuscript presents a new individual-technology fit framework and explores the links between individual characteristics and biometric interface technologies for explaining performance. Finally, the manuscript outlines an approach called a *biometric user profiling* process for deriving comprehensive user profiles that may be used to explain individuals' performance with biometric interface technologies. In this work, performance is measured by *BioGauges* (Adriane B. Randolph, Moore Jackson, & Mason, 2007), a methodology and toolset for objectively measuring user controllability of biometric interface technologies. Individual-technology fit is explored with two biometric interface technologies.

2. Motivation and Background

One out of five people in the United States has a *disability* (Social Security Administration, 2003), which is a long-lasting impairment prohibiting what society considers normal activity (World Health Organization, 1980). A disability is classified according to six categories including: sensory, physical, mental, self-care, difficulty going outside the home, and employment disability (Waldrop & Stern, 2003). Physical disabilities can be understood along a continuum ranging from the retention of fine motor control by able-bodied individuals to the loss of all voluntary movement and speech, termed *locked-in*. Half a million people worldwide are considered locked-in, essentially prisoners in their own bodies (National Organization for Rare Disorders (NORD), 2000). A person may become locked-in due to diseases such as amyotrophic lateral sclerosis (ALS – also known as Lou Gehrig's disease), spinal cord injury, or brain-stem stroke. Although they have lost the ability for unaided control of their environment, locked-in persons are generally cognitively intact but this state may deteriorate over time (Ariniello, 1999).

Figure 1 illustrates this continuum of disabilities and the input devices most commonly used at each stage.

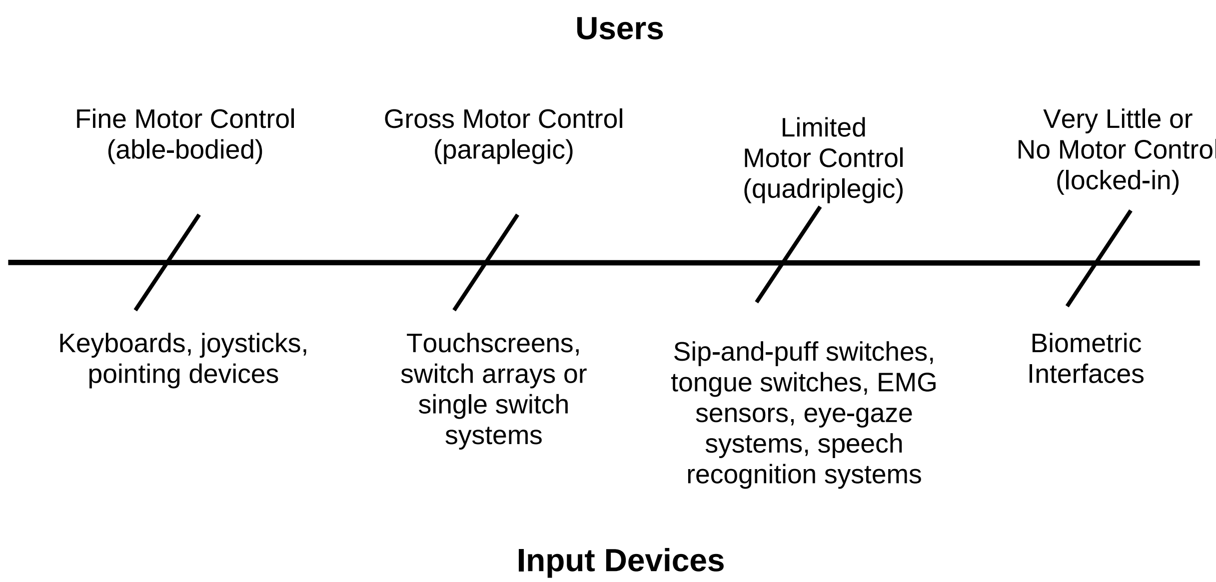

Figure 1. A continuum of disabilities and control interfaces.
Figure adapted from (Moore, Storey, & Randolph, 2005).

Figure 1 also lists various technical options that aid disabled persons and help improve their quality of life. However, more work is needed to make the interfaces less obtrusive for users and the people with whom they interact. A way to achieve this goal is by better matching the related technologies to users based on individual characteristics. In particular for people with severe motor disabilities, it would be advantageous to know which biometric interface technologies are most effective based on a profile of their individual characteristics. If these individual characteristics were indicators of a person's capabilities for control of biometric interface technologies, they could be linked to features of the technology to explain performance and ultimately improve biometric interface design.

The following provides background on the forerunning biometric interfaces that are currently available, key considerations for users of assistive technology, and how these may be measured and modeled.

2.1. Biometric Interfaces

Historically, the term *biometric* referred to the mathematical and statistical analysis of agricultural and atmospheric effects on humans, but more recently it has been associated with a physiological measure used for personal verification and security applications (Biometric Consortium, ; International Biometric Society, 2002). Here, the term biometric is more generally defined as a measure of a physiological response that is not based on muscular control. A *biometric interface* is the resulting system when biometrics are incorporated as input to assistive technologies. A *brain-computer interface (BCI)* is a type of biometric interface that specifically utilizes measures of brain activity as input.

Evolving from medical diagnostic systems, biometric interfaces are now also investigated in the assistive technology and HCI fields. Traditionally, the targeted users are locked-in, but people who have movement disorders (e.g., severe cerebral palsy patients) or operate within situations that temporarily induce a movement disability (e.g., jet pilots) may also find biometric interfaces useful.

Research in the field of biometric interfaces spans several disciplines including computer science, electrical engineering, cognitive psychology, neuroscience, and information systems all working to discover the most appropriate alternatives for users with severe physical impairments. Although biometric interfaces have yielded working applications based on non-muscular input for control, they currently only reach a maximum information transfer rate of 68 bits/minute (i.e., 9 characters/minute is possible with a predictive program) and trade off speed and accuracy for number of choices possible (Gao, Xu, Cheng, & Gao, 2003). Despite this performance, these systems lend great hope to people who otherwise may not have another outlet.

There are several approaches to recording the signals which serve as input to biometric interfaces although it is not yet clear which approach works best for a particular person for control. This work focuses on *non-invasive* techniques which involve sensors placed on the skin's surface for signal acquisition instead of surgically-implanted devices. The most common of these approaches is electroencephalography (EEG), a bio-recording technique to measure electrical activity of the brain, collected from scalp electrodes. Another approach includes the use of functional magnetic resonance imaging (fMRI) as a non-invasive method for measuring oxygenated blood volume using a powerful, magnetized probe that can reflect activity throughout the brain. Other approaches include galvanic skin response (GSR) for measuring skin conductance and functional near-infrared (fNIR) for also measuring oxygenated blood volume in the brain but using near-infrared light reflections. The following describes in greater detail the two biometric interface approaches used in this work: fNIR and GSR.

2.1.1. Functional Near-Infrared Imaging

In addition to the more widely examined electrical brain activity, researchers are beginning to explore another process of the brain, oxygenation of blood, as input to biometric interfaces (Stenger, 2005; Weiskopf et al., 2004). Oxygenation of blood is a reflection of vascular activity that has a 3 to 7 second delay and only indirectly reflects brain activity. Near-infrared spectroscopy (NIRS) is a process used to measure changes in oxygenated blood volume on the surface of the brain resulting in what is called functional near-infrared (fNIR) imaging. A device such as Archinoetic's Optical Tomographic Imaging Spectrometer (OTIS) illustrated in Figure 2 may be used for fNIR sensing. In this process, near-infrared light is used to non-invasively penetrate the scalp and skull and is absorbed by oxygen carriers within the bloodstream, or hemoglobin. The person on the right of Figure 2 shows how the sensor may be placed on the surface of the head to detect blood volume in different areas of the brain. Different functions such as counting or moving a finger (Kleinschmidt et al., 1996) alter the amount of oxygen being absorbed at a given time and may allow a biometric interface to be controlled.

Figure 2. The OTIS fNIR device and sensor placement.
Photo on left used with permission from (Nishimura et al., 2006).
Photo on right taken by Stanley Leary and used with permission.

2.1.2. Galvanic Skin Response

Whereas a BCI is based on activity recorded from the brain, *galvanic skin response (GSR)* is a measure taken non-invasively of the electrical conductivity of the skin. Although the electrodes may be placed anywhere, a typical configuration for a GSR device includes two electrodes placed on the index and middle fingers, areas of the skin with the most active sweat glands, as illustrated in Figure 3. The device sends an imperceptibly small amount of electrical current through the electrodes to measure the momentary amount of skin conductivity created in response to various stimuli or the person's own imagery.

Figure 3. Example configuration for GSR electrodes.
Modified from Michael Gasperi's website (http://www.extremenxt.com/gsr.jpg).

The measurable change in electrical skin conductivity for GSR is caused by increased activity in the sweat glands due to stimulation to the Sympathetic Nervous System (SNS), as when a person is anxious or excited (Abrams, 1973). The GSR procedure was first used for psychiatric evaluation (Jung, 1907), and was later adopted for interrogation purposes by law enforcement officials as a component of polygraph testing (Committee to Review the Scientific Evidence on the Polygraph & National Research Council, 2003). First, the system takes a baseline reading of GSR. Then, it monitors the person for significant changes in his or her GSR levels from that baseline according to different stimuli or imagery. For example, the person may be asked to talk about a particular incident (as with interrogation), watch different visual stimuli, or think of an image. With lie-detection, a trained polygrapher then interprets the changes in GSR levels during that recording session generally in an offline context. However, with computer applications such as video games and communications systems, the associated computer system analyzes the differences in real-time and provides immediate feedback to the user (Moore & Dua, 2004; Sakurazawa et al., 2003). Although GSR is popularly identified with lie-detection, assistive technology researchers are investigating uses for control of computer-based systems (Moore & Dua, 2004; Adriane B. Randolph, McCampbell, Moore, & Mason,

2005) as an alternative to neural control which has been found ineffective for some users (Birbaumer & Hinterberger, 2003).

2.2. Biometric Interface Design

Although biometric interfaces have largely been studied in laboratory settings, there is little work that provides general characterizations of the biometrics and how they relate to the users generating the biometric phenomenon. In addition, there is currently no formal method for assessing what biometric interface technology is most appropriate for a user. For example, current BCI community practices and underlying technical infrastructures do not easily allow for a comprehensive set of tests to determine the most appropriate means for signal control for a locked-in user. Therefore, users often only benefit from the approach offered by their attending team which may not be the optimal choice.

Researchers have explored the design of neurologically-based biometric interface technologies from a system perspective (Mason & Birch, 2003). A full assistive technology system as described by Mason et al. (2005) includes a biometric transducer, a control interface, and an application or assistive device linked through the device controller. Figure 4 illustrates the components of a full assistive technology system which may also be used to represent the components of a full biometric interface system. The portion of the system that performs the signal acquisition and filtering is called the *transducer*. The transducer outputs a low-level, machine-readable interpretation of the signal that the system may then use to talk with a control interface. A control interface translates the low-level interpretation into one that can be used by an application or device. Biometric transducers are characterized according to their form of output (e.g., spatial reference, discrete, or continuous form) (Adriane B. Randolph, Moore Jackson, Mason, & McCampbell, 2005).

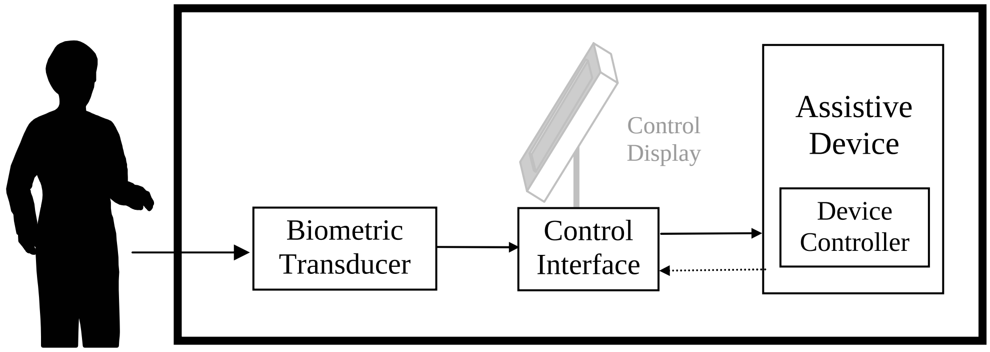

Figure 4. A model of a full biometric interface system.
Adapted from (Mason & Birch, 2003; Mason et al., 2005).

2.3. Assistive Technology

The term *assistive technology* refers to devices that seek to "increase, maintain, or improve the functional capabilities of individuals with disabilities" (U.S. Congress, 1998). Biometric interface technologies such as those relying on measured input from the brain and GSR are a part of *assistive technology systems* which include an assistive technology device, a user with an inherent or induced disability, and the environment within which a particular task is performed (Cook & Hussey, 2002).

2.3.1. The Human Activity Assistive Technology Model

There has been an increasing awareness that the challenges faced by people with disabilities are not the result of the disability itself but rather a combination of the disability and the environment within which that individual operates (Brandt & Pope, 1997). This environment or context includes considerations for: (1) setting; (2) social context; (3) cultural context; and (4) physical context (Cook & Hussey, 2002). *Setting* includes the location and related conditions such as the task to be accomplished and rules surrounding completion of that task. *Social context* governs what is considered "normal" or "expected." *Cultural context* relates to concepts of shared patterns of behavior and how individuals interact with others and the environment. Finally, *physical context* describes the environmental conditions where the system is situated, and commonly includes measures for heat, light, and sound. Together with context, three other components join to make up the Human Activity Assistive Technology (HAAT) model (Cook & Hussey, 2002), modified from a general model for human performance (Bailey, 1982), both illustrated in Figure 5. The additional three components include the individual, the activity they wish to perform, and the technology assisting him/her in that activity all taking place within a particular context.

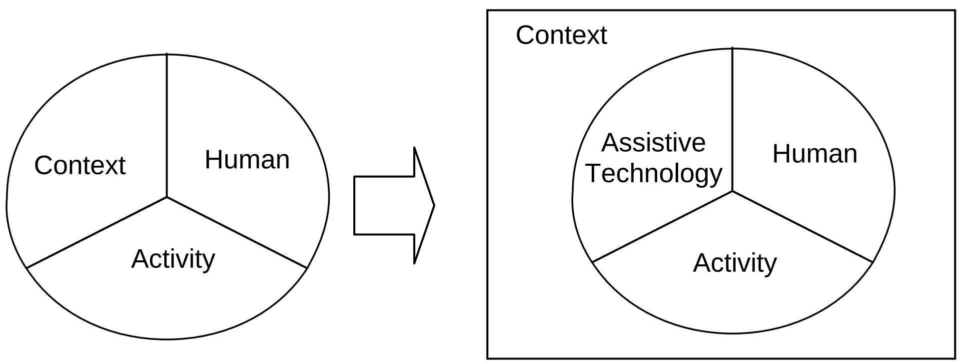

Figure 5. Relationship between the Human Performance Model and the HAAT Model. Modified from (Bailey, 1982) and (Cook & Hussey, 2002).

Figure 6 illustrates a proposed model for describing the interacting influences of the transducer, user, and environment on biometric system design as supported by the HAAT model. Researchers have largely focused on the hardware and software aspects included in the transducer component of biometric interface systems (Mason & Birch, 2003) but have not thoroughly examined the characteristics of the user and the environment in which the system is used. All three components together influence biometric interface design and must be examined in depth to determine the appropriate technology for a user. This work focuses largely on the characteristics of the user and his or her interactions with the transducer.

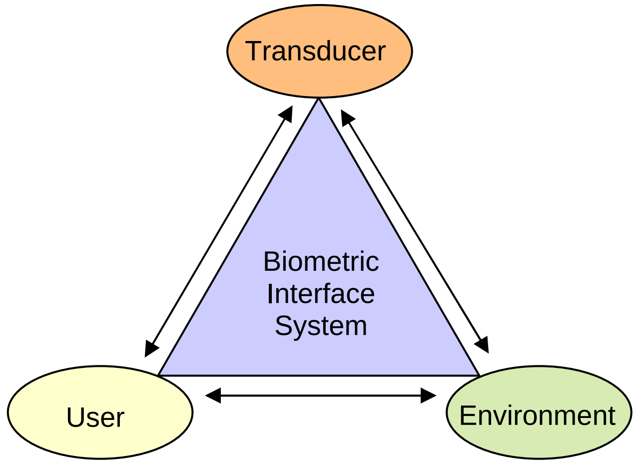

Figure 6. Proposed model of components of biometric interface system design

The HAAT model emphasizes the need to assess human ability within the context of the environment where the task will be performed or else there may be a misrepresentation. For example, a jet pilot has so many displays to monitor that he or she may experience a sensory disability because his or her sight is overloaded, thus creating the need for another input channel. Without considering the environment, the pilot may be modeled as an able-bodied person which would be an inaccurate assessment. Other models such as the keystroke-level model (KLM) (Card, Moran, & Newell, 1980) and the three-state model (Buxton, 1990) provide an understanding of humans operating various devices, but they consider physical movement which is not applicable for biometric interfaces.

2.3.2. The U.S. Institute of Medicine's Model of Disability

The human component of the HAAT model is based on *intrinsic enablers* that characterize inherent abilities an individual uses to perform a task. These intrinsic enablers include: (1) sensory input; (2) central processing; and (3) effectors and are a combination of psychological and physical capabilities or limitations. Such abilities (or lack thereof) may be modeled using the “Conceptual Overview of the Enabling-Disabling Process” from the U.S. Institute of Medicine’s (IOM) model of disability (Brandt & Pope, 1997) as reproduced in Figure 7. This model illustrates the effect a disability has on an individual operating within his or her environment.

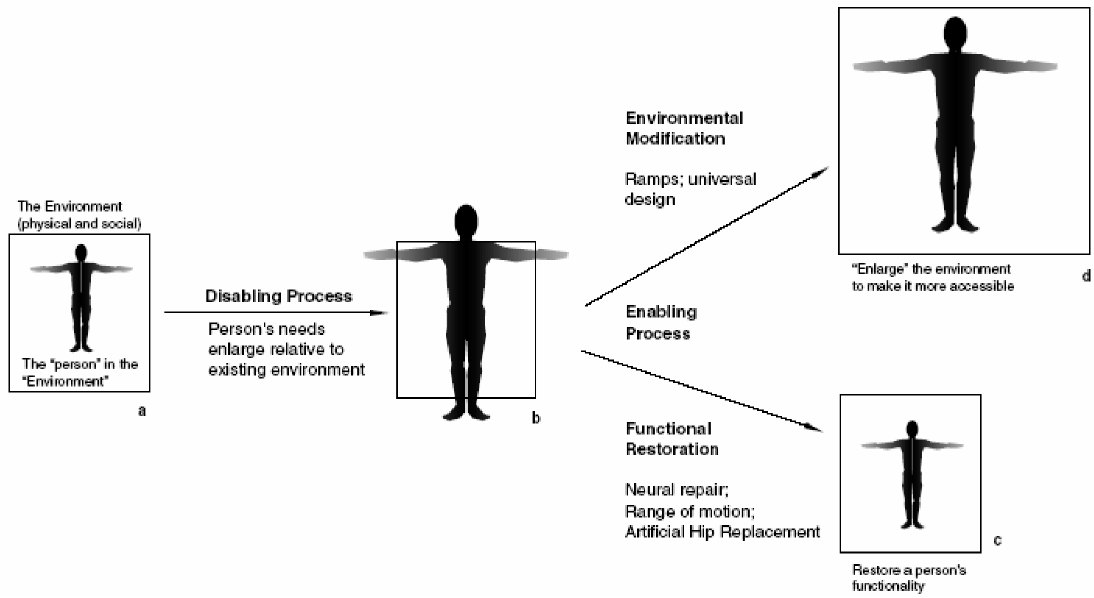

Figure 7. Conceptual overview of the Enabling-Disabling Process.
Used with permission from (Brandt & Pope, 1997).

2.3.3. The ALS Functional Rating Scale

It is helpful to measure human abilities using an established scale. In the case of measuring abilities for people with ALS, the ALS Functional Rating Scale (ALSFRS) (Amyotrophic Lateral Sclerosis Ciliary Neurotrophic Factor Treatment Study (ACTS) Phase I-II Study Group, 1996) may be used. This rating scale allows an assessor to assign points to various levels within the following ten categories as illustrated in Figure 8, where a zero assigned for some categories, such as speech, would indicate that the person is completely locked-in:

1. speech
2. salivation
3. swallowing
4. handwriting
5. cutting food and handling utensils (with or without gastrostomy)
6. dressing and hygiene
7. turning in bed and adjusting bed clothes
8. walking
9. climbing stairs
10. breathing

Measure	Finding	Points
speech	normal	4
	detectable speech disturbance	3
	intelligible with repeating	2
	speech combined with nonvocal communications	1
	loss of useful speech	0
salivation	normal	4
	slight but definite excess of saliva in mouth; may have nighttime drooling	3
	moderately excessive saliva; may have minimal drooling	2
	marked excess of saliva with some drooling	1
	marked drooling; requires constant tissue or handkerchief	0

Figure 8. Sample of the ALS Functional Rating Scale.
Modified from (Amyotrophic Lateral Sclerosis Ciliary Neurotrophic Factor Treatment Study (ACTS) Phase I-II Study Group, 1996).

Table 1 proposes how each of the measures relates to the use of traditional assistive technologies which rely on some degree of muscular control. Similar to how they indicate the need for traditional assistive technologies, these measures may indicate the need for a biometric interface. However, it is unknown how they might relate to a user's performance when using a biometric interface technology.

Table 1. Proposed relationship of ALSFRS measures to use of traditional AT

No.	Measure	Relationship to Traditional AT Use
1.	Speech	Reflects ability to use speech-activation or recognition for control
2.	Salivation	Unknown
3.	Swallowing	Reflects ability to use controlled, detectable movement to activate a switch
4.	Handwriting	Reflects ability to use stylus-type devices
5.	Cutting food and handling utensils (with or without gastrostomy)	Reflects degree of fine motor control needed to type or move a mouse
6.	Dressing and hygiene	Reflects degree of motor control and independence possibly necessitating AT use
7.	Turning in bed and adjusting bed clothes	Reflects degree of motor control and independence possibly necessitating AT use
8.	Walking	Reflects need for device that assists with ambulation
9.	Climbing stairs	Reflects fatigability with gross motor movement
10.	Breathing	May use controlled breaths to make activations such as needed with sip-and-puff switches

Although the HAAT model emphasizes the overall interplay between human (abilities), technology, and activity as a type of human performance model, it does not indicate which aspects have the most influence on performance. This link is needed to improve biometric interface design. In fact, when designing based on the underlying Human Performance Model, it is necessary to consider the separate parts as well as the combined elements. In particular, designers should focus on the most complex element, the human, whose widely ranging characteristics can alone affect human performance (Bailey, 1982). Other factors that affect user interface design are further discussed in the next sections.

2.4. User Profiling

Research on profiling and ways to more effectively incorporate information about the system user were proposed to help overcome problems of ineffective interfaces. *User profiling* is a way to allow information filtering based on a user's personal characteristics and is often used interchangeably with the term user modeling (Hanani, Shapira, & Shoval, 2001). The term user profiling is overloaded. It has been described as taking a content-centered approach by capturing information about a person's habits and taking a user-centered approach that focuses on particular user traits or characteristics. Most commonly, user profiling is conducted in online communities using the content-focused approach. Well-known websites such as Amazon.com and Yahoo! employ profiling to better understand their users' needs and provide customization and personalization. Whenever someone establishes a new account with an online service, a type of user profile is created. User-centered profiling such as how Jameson (2001) describes it, takes into account both current state and long-term characteristics of the user combined with environmental context. Current state characteristics included aspects of the user's current cognitive or psychological state such as current level of emotional arousal. Longer-term characteristics included: objective personal characteristics; level of knowledge of particular topics; level of interest in particular topics; and perceptual and motor skills and limitations. This work applies this definition for user profiling.

Knowledge about the user for populating the profile may be acquired via explicit or implicit means. An *explicit* approach requires active user involvement to provide the information. One of the most popular techniques of the explicit approach is user interrogation where users are asked to complete questionnaires about themselves or select from a predefined set of profiles (Hanani et al., 2001). User interrogation began with the Lens system (Malone, Grant, Turbak, Brobst, & Cohen, 1987) to define a set of rules with which to filter information. In contrast, an *implicit* approach requires no direct action or involvement by the user. The system records the user's behavior and makes inferences about the relevancy of information based upon the user's reaction (Hanani et al., 2001).

2.5. Fit

The words "link" and "match" used in the introduction of this manuscript are synonymous with the word "fit". The theoretical concept of *fit*, used to describe contingent relationships between variables, is classified according to six perspectives (Venkatraman, 1989): moderation, mediation, matching, gestalts, profile deviation, and covariation described as:

- *Fit as moderation* – An interaction between two variables that affects a third variable.
- *Fit as mediation* – How a variable intervenes between an antecedent and its consequent variable.
- *Fit as matching* – A theoretical match between two variables without specific regard to a criterion variable although effect on a third variable may be measured.
- *Fit as gestalts* – Internal coherence to frequently recurring clusters of attributes.
- *Fit as profile deviation* – Degree of adherence to an ideal, externally specified profile.
- *Fit as covariation* – Internal consistency reflecting an underlying thread that logically relates variables.

Fit as moderation, mediation, and matching specify a relationship typically between just two variables, and fit as gestalts, profile deviation, and covariation specify a relationship typically between multiple variables.

The concept of fit has been used widely throughout the management literature. It has been applied to business organizations using fit as matching by pairing individuals with psychological situations and observing behavior (Joyce, Slocum, & Glinow, 1982) and by pairing certain business strategies with company structure and observing company performance (Chandler, 1962).

The concept of fit has also been applied to information systems by linking tasks to technology features in a manner affecting performance with fit as an ideal profile (Zigurs & Buckland, 1998) and with fit as moderation (D.L. Goodhue, 1995; Dale L. Goodhue & Thompson, 1995). According to the fit as moderation perspective, the concept of *task-technology fit (TTF)* most closely aligned with the aims of HCI and was defined as "the extent that technology functionality matches task requirements and individual abilities [and] …is presumed to lead to higher performance" (D.L. Goodhue, 1995, page 1829). There, the word "match" was used to describe how technology features are moderated by task requirements and individual characteristics to predict performance impacts. Performance has typically been analyzed for able-bodied individuals with traditional interfaces and models have largely ignored the impacts of disability.

Goodhue and Thompson's (1995) model of the Technology-to-Performance Chain (TPC) as shown in Figure 9 initially considered individual characteristics as a component affecting TTF but only tested a subset of the model and did not include this construct.

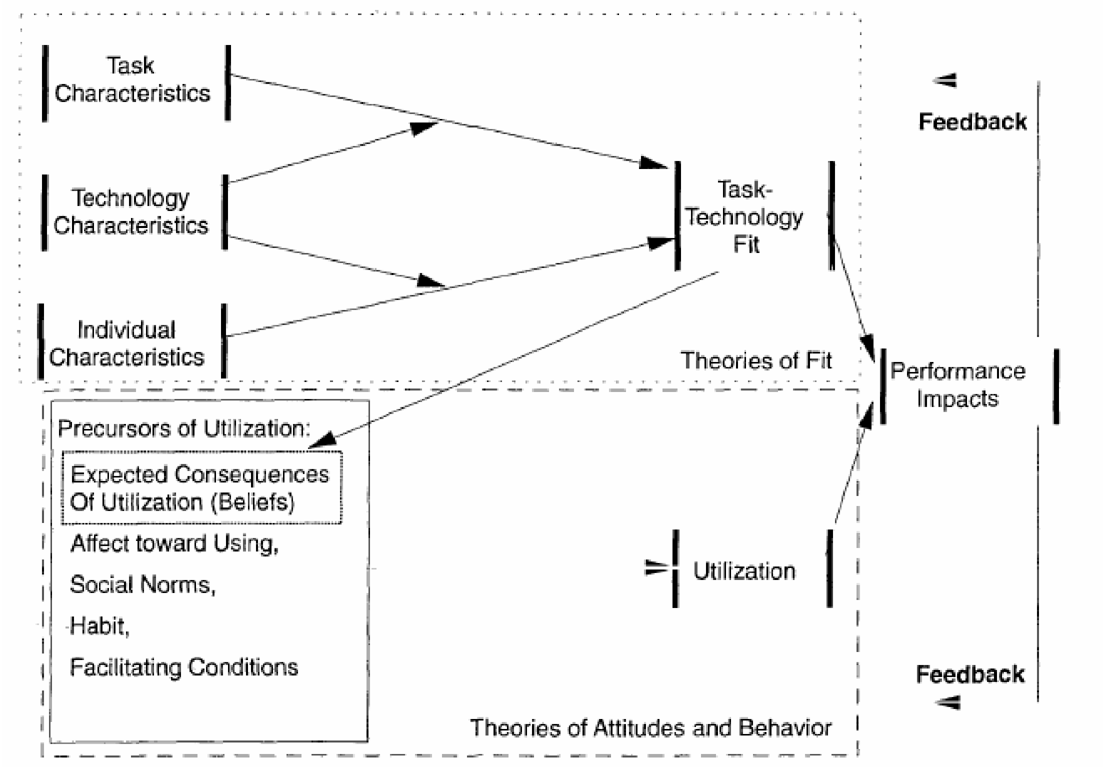

Figure 9. The Technology-to-Performance Chain Model.
Used with permission from (Dale L. Goodhue & Thompson, 1995).

However, Goodhue (1995) tested the effect of individual characteristics on TTF using the model shown in Figure 10. Here, individual characteristics were represented with a single feature: computer literacy. Analysis of the data showed that an individual's level of computer literacy had an effect on TTF. User evaluations of TTF served as a surrogate for the objective measure of TTF. Analysis also uncovered inconsistencies in results of the assertion that more computer literate individuals would find that systems more completely address their needs; this assertion was only true for system reliability but not for other dimensions of TTF such as locatability of data. This implies that a more robust construct for individual characteristics is needed.

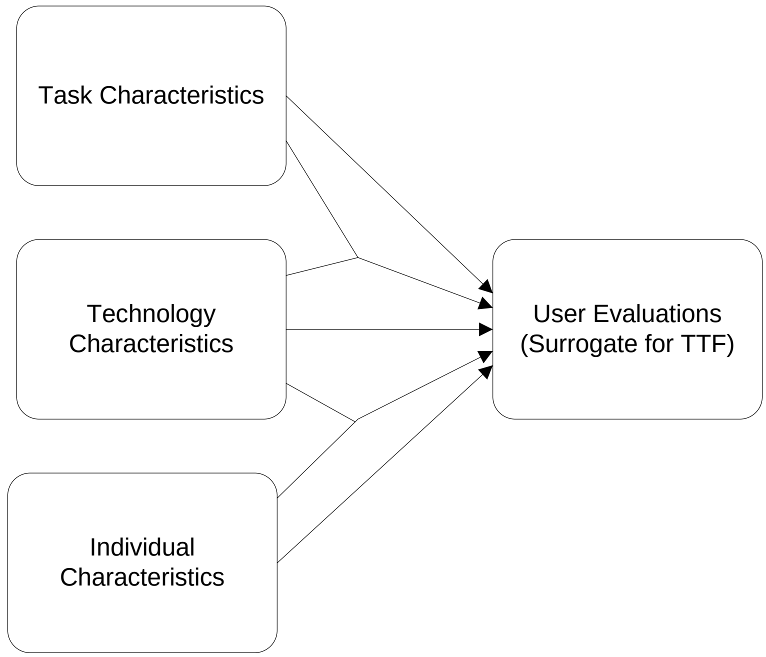

Figure 10. Upstream determinants of user evaluations of task-technology fit. Adapted from (D.L. Goodhue, 1995).

Others exploring the concept of TTF in MIS consider TTF to be a function of task characteristics and technology characteristics with perhaps other moderating variables (Dishaw & Strong, 1998) but have not incorporated the construct of individual characteristics. Therefore, further investigation is needed for incorporating the construct for individual characteristics into models considering the concept of fit. It was not clear if computer literacy should have been the sole descriptor of an individual and whether or not other characteristics might have had greater and more consistent impacts on TTF. In addition, Goodhue's model only examined TTF according to self-reports from users of performance and did not link individual characteristics to measures of actual performance.

3. Theoretical Framework

This work describes a new framework for individual-technology fit (ITF) as illustrated in Figure 11 which seeks to initially link individual characteristics and features of biometric interface technologies with human performance using a fit as matching perspective. This framework is a modified version of Goodhue's models of TTF (Figures 9 and 10). This work is focused on the discovery and exploration of fit between individual characteristics and biometric interface technology. This framework is investigated with the GSR (amount of sweat) and fNIR (amount of oxygenated blood volume) biometric interface technologies. Through this study, expertise will be created and used for future investigations.

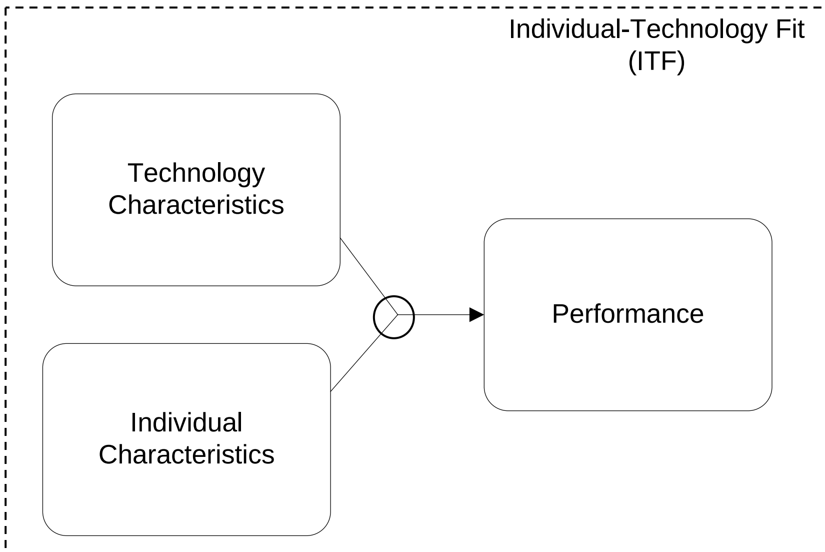

Figure 11. Proposed framework of individual-technology fit

The ITF framework does not include utilization because utilization of biometric interface technology may be considered mandatory for locked-in users if they have no other alternatives and a strong desire for communication and control. "When utilization is mandatory, it does not need to be considered" (D.L. Goodhue, 1995, page 1830). Furthermore, utilization considers ongoing use and this ITF framework is for explaining initial performance. In addition, task is not included because it is held constant in an effort to focus on the impact of individual characteristics with technology features. The following sections describe the components of the proposed ITF framework in greater detail.

3.1. Individual-Technology Fit

Similar to the definition for task-technology fit, *individual-technology fit* is the extent to which individual characteristics match with technology features to enable a person's control of a technology. Here the context is biometric interfaces. Specifically, ITF is the correspondence between individual characteristics and the biometric interface technology being used. A strict interpretation of the original task-technology fit model is not applicable here because there are no true experts that exist to determine fit a priori or independently of performance; it does not appear that any researcher or manufacturer is suited to provide an external measure of fit because this technology is only beginning to be investigated for control purposes and few users have sufficient experience with these technologies or alternative biometric technologies to understand their own fit.

3.2. Technology Characteristics

The technology features of biometric interfaces are based on a taxonomy of brain-computer interfaces and attributes of a transducer (Mason et al., 2005) which should include the following:

1. *Type* – Classification of the general mechanism used (i.e., endogenous, exogenous, or modulated response). An *endogenous* type of transducer has internally generated control versus an automated response to external stimuli, such as used with *exogenous* types, or an internal modulation of external stimulation, such as used with *modulated response* types.
2. *Biorecording Technology* - Approach used to record signals from the participants (e.g., EEG, fNIR, fMRI, GSR).
3. *Inputs* – Placement of sensors/electrodes (e.g., areas over the brain, fingers).

4. *Biometric Phenomenon* – Phenomenon used to control the biometric transducer (i.e., phenomena in electrical brain activity, phenomena in blood oxygenation, or phenomena in skin conductance).
5. *Stimulator* – If applicable, the stimulus used for cueing exogenous transducers.
6. *Feature Extraction/Translation Algorithms* – Component that extracts and translates the signal into a useful control signal.
7. *Output* – Type of transducer output (i.e., discrete, continuous, or spatial reference). Discrete transducers produce output in a set of states, such as a switch; continuous transducers produce an ongoing stream of output within a range; and spatial reference transducers produce output in a particular point in 2-D or 3-D space that can be selected.
8. *Idle Support* – Indication of whether the transducer supports a state where the user is not intending to control the technology (i.e., No Control State).

This study considered just one feature of the transducer, biorecording technology (fNIR or GSR), as the distinguishing factor between the biometric interface technologies being compared. Of the other seven features of the transducer three were held constant to narrow the scope of this work (endogenous type, continuous output, and idle support in the form of a “rest” state); three had a one-to-one correlation with the biometric technology tested (biometric phenomenon, inputs, and the feature extraction/translation algorithms); and one was not applicable per the experimental protocol (stimulator).

3.3. Individual Characteristics

Individual characteristics are the distinguishing factors between people and include their demographic, physiological, and cognitive differences. Little is known about which individual characteristics best match with particular biometric interface technologies although there are numerous assessments of human capabilities ranging from functional limitations to the amount of system training received.

Table 2 lists and provides cited justifications for a proposed set of characteristics affecting biometric interface technology control. This list is based on a review of related literature and discussions with researchers in the fields of biometric interfaces and assistive technology concerning observed or plausible physiological effects. Although characteristics such as age change over time and vision may degrade for locked-in users, these characteristics generally remain constant for more than a few days and may be considered more stable. In addition, there are more dynamic characteristics of an individual such as the amount of sleep and recent intake of caffeine that may significantly affect performance. These dynamic or momentary characteristics can vary so much over a short period of time that it is difficult to use them as stable constructs, so their potential effects are noted through the use of a session questionnaire.

Table 2. Proposed individual characteristics to test

Category	Attribute	Justification for Inclusion
Demographic Trait	1. Sex	There are a number of physiological and spatial reference differences based on sex. For example, sex may be a key factor for GSR-based control since skin conductivity is based on the amount of sweat; although women have more sweat glands than men, men's sweat glands are more active (Medline Plus, 2006).
	2. Age	Age moderates various physiological differences. For example, older people (age 52 +/- 10 years) have lower increases in localized levels of oxygenated blood (Hock et al., 1995).
	3. Handedness	Human handedness relates to location of the language center in the brain where this center is generally located in the left, front hemisphere but sometimes found on the right for left-handed individuals (Annett, 1985, 2001). A common protocol for fNIR recordings is to place the sensor over the left hemisphere Broca's area for language production (Nishimura et al., 2006).
Physiological Trait	4. Athleticism	Athletes' cardiovascular systems respond differently from the average population and from people with limited motor functions, such as people with quadriplegia (Patil, Karve, & DiCarlo, 1993). This difference may affect performance with a system based on vascular responsiveness.
	5. Smoking Experience	Limited exposure to nicotine has been shown to increase parietal activity (Giessinga, Thiela, Röslerc, & Fink, 2005) and people classified as smokers have increased cerebral blood flow velocity (Terborg, Birkner, Schack, & Witte, 2002).
	6. Paralysis	Studies have shown that the strength of electrical signals from

Category	Attribute	Justification for Inclusion
		sensorimotor cortex activity weakens as physical ability declines (Tran, Boord, Middleton, & Craig, 2004).
	7. Hair Color	Collaborators using fNIR technology have shared anecdotal evidence of difficulty calibrating their systems with individuals with darker hair color.
	8. Skin Color	Collaborators using fNIR technology have shared anecdotal evidence of difficulty calibrating their systems with individuals with darker skin color.
	9. Hair Texture	Collaborators using fNIR technology have shared anecdotal evidence of difficulty calibrating their systems with individuals with thicker hair.
Cognitive Trait	10. Prior Training with Biometric Interfaces	The amount of hours of training with particular BCIs affects a person's ability to control electrical signals such as those from sensorimotor cortex activity (Wolpaw et al., 2002). It is possible that training with a biometric interface technology increases kinetic intelligence (Gardner, 1993) and thus will improve overall performance with any biometric interface technology.
	11. Video Game Experience	High-speed interactive video game players versus non-high-speed interactive video game players experience changes in their visual attention (Green & Bavelier, 2003), a key factor for visually-evoked potentials (VEPs) recorded through EEG. It is possible that experience with particular types of video games will also impact performance with other biometric interface technologies.
	12. Computer Use	A person's self-reported assessment of his or her aptitude for using basic computer applications was found to affect IS performance (D.L. Goodhue, 1995).
	13. Acting Experience	There is an acting method pioneered by Konstantin Stanislavski called "Method Acting" where actors learn to express their character's emotions based on recollection of actual emotions felt in the past (WordNet).
	14. Meditation Experience	By using techniques such as the Transcendental Method for meditation, people are trained to focus their minds and produce calm states (Yogi, 2005).

3.4. Performance

Here, performance is the observable evidence of fit between individual characteristics and a particular biometric interface technology. As individuals are better matched to biometric interfaces, their performance should increase and vice-versa if ill-matched. In this study, performance is defined as the proportion of successful attempts out of overall attempts by a user to achieve a prescribed goal using a particular biometric interface technology.

4. Method

4.1. Research Design

The *biometric user profiling process* was developed as an approach for deriving comprehensive user profiles that may be used in conjunction with the ITF framework to explain individuals' performance with biometric interface technologies. This study investigated ITF of the characteristics proposed in section 3.3 with the fNIR and GSR biometric interface technologies. All participants were tested with each selected biometric interface technology twelve times. Aside from distinctions based on motor control, groups could not be established ahead of time because individual characteristics for people cannot be manipulated. Therefore, there was no explicit control set up as typically conducted with between-group tests; rather the control was elicited within each person. According to the design details, this study is considered to be a *non-experiment* because it did not employ random assignment or a control group (Trochim, 2001).

The scope of this work was narrowed based on sample population and application area. Purposive sampling was used to gather participants with a range of motor disabilities brought on by ALS and who had a wide range of ages beyond what is typically achieved with a university student population. *Purposive sampling* involves taking a sample of people from a targeted group to ensure their participation (Trochim, 2001). In this study, it was necessary to gain participants who suffered from severe motor disabilities and who represented a wide range of ages such as found in the target population for biometric interfaces. The timeframe for explanation covered the person's initial state in using the technology because user needs change over time (Hanani et al., 2001). This work focused on the person's initial use of the technology and not his or her intention for future use. Therefore, training effects were not considered.

4.2. Participants

The study included 38 adult participants (33 able-bodied and 5 disabled) with a range of prior experience using a biometric interface. Overall, the ages ranged from 21 to 67 with an average of 39 years, and there were 13 females and 25 males. Participants included undergraduate students, graduate students, trade workers, and working professionals. Appendix A provides details about the participants. Specific differences in characteristics are presented and analyzed in the results section. To narrow the focus of the population, users were cognitively intact with a range of physical disabilities not including total loss of sight or hearing. All participants were recruited via word-of-mouth or were referred by friends to participate in the study. Sessions with able-bodied participants were conducted in the Georgia State University and Georgia Institute of Technology BrainLabs. Sessions with disabled participants were conducted in their homes with steps taken to provide a controlled atmosphere similar to the lab setting by requesting a quiet environment away from streaming sunlight.

4.3. Apparatus

The approaches for signal collection selected for this work were GSR and fNIR to enable objective cross-comparisons between results since both produced continuous output. In addition, these approaches were portable and relatively easy to operate due to the related hardware and non-invasive approaches. The complete system setup with GSR is illustrated in Figure 12. A standard laptop was used to run the BioGauges system shown on the left-most laptop and a separate laptop was used to run the biometric recording software for fNIR and GSR shown on the right-most laptop. The components of each biometric system are outlined as follows.

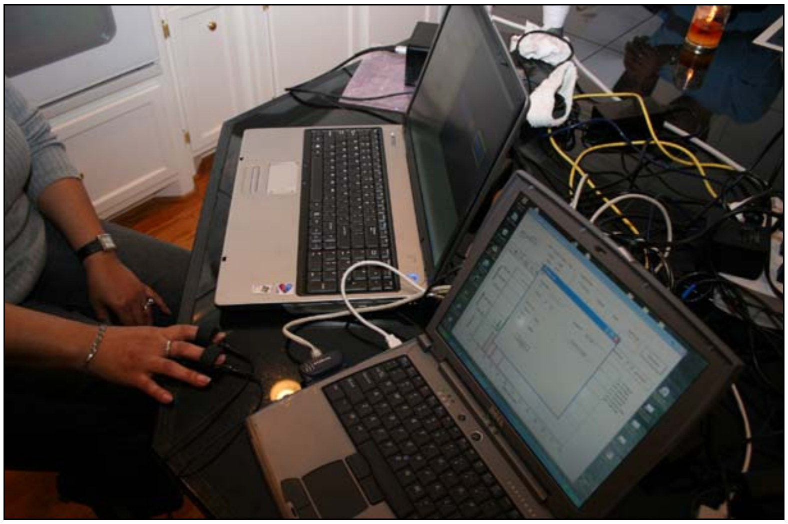

Figure 12. Complete experimental system setup

GSR Recordings:

- Lafayette Instrument Company DataLab 2000 biometric recording system (www.lafayetteinstrument.com):
    - DataLab 2000 software version 1.3
    - General Purpose Interface Bed model 70701
    - Biopotential amplifier model 70702 with a signal range of +/- 10V, a fixed gain of 5000, and built-in calibration values of +/- 4mV
    - Two metal plate electrodes for placement on the index and middle fingers
- National Instruments Data Acquisition (NI-DAQ) hardware version 7.1.0 (www.ni.com)

fNIR Recordings:

- Archinoetics fNIR recording system (www.archinoetics.com):
    - OTIS™

- Pucklink software version 2.2
- Sensor with one infrared emitter and two detectors arranged in a fixed triangular shape with each surrounded by foam padding to add comfort and reduce light scatter

- Standard size tennis headband to hold fNIR sensor in place on head over left dorso-lateral prefrontal cortex (DLPFC) (left temple area on the head)
- Participant seated away from directly streaming sunlight

4.4. Capturing Individual Characteristics

Individual characteristics may be used to populate a *biometric user profile* which is a representation of the most salient features of a user for explaining performance with biometric interface technologies in a concise representation. A biometric user profile was first outlined in the work conducted by Davis (Randolph) et al. (2003) to indicate communication topics for use with a biometric interface. Although the attributes differ slightly when used for explanation of performance with a biometric interface technology, the process for populating the values remains the same. This previous work revealed that when initially setting up user profiles, as for a conversational system for a severely disabled user, an explicit approach should be implemented (Moore, Storey, Davis, & Napier, 2004). Therefore, a questionnaire was appropriate for obtaining the sample biometric user profile values illustrated in Table 3.

Table 3. Sample biometric user profile for one locked-in patient

Category	Attribute-Value Pair
Demographic Traits	Sex = male Age = 45 Handedness = right
Physiological Traits	Athleticism = 1-low Smoking Experience = no Motor Control = very little Skin Color = 1-white Hair Color = 2-brown Hair Texture = 3-curly Affective Drugs = yes Regular Caffeine = no Regular Alcohol = no Head Injury = no Hand Dexterity = yes Played Sports = yes
Cognitive Traits	Prior Biometric Training = extensive Video Game Experience = none Computer Use = extensively Acting Experience = none Meditation Experience = none Years of Education = 16

A questionnaire was devised for explicitly obtaining the values for each property of the biometric user profile while keeping in mind temporary influences (e.g., possible sleep deprivation, biological rhythms, illness) and vasoactive agents (e.g., stimulants such as caffeine) which could significantly affect the performance of participants (Alluisi & B.B. Morgan, 1976; Liu et al., 2004). The questionnaire underwent pilot testing with two able-bodied users and a researcher experienced with ALS patients to ensure content validity. Each participant completed the biometric user profile questionnaire and session information sheets provided in Appendices B and C.

4.5. Measuring Performance

After completing the questionnaires about their individual characteristics and momentary influences, the researcher verified correct positioning of the biometric sensor and calibrated the recording system. For GSR, the sensors were always cleaned with an alcoholic-based gel and then placed on the pads of the index and middle fingers of the right hand and secured by Velcro. Then, the DataLab 2000 software provided an end-to-end calibration of the recording system. For fNIR, the Pucklink software's Signal Quality Assessment tool was used to verify correct sensor placement by when it achieved an accurate heart rate and a heartbeat signal-to-noise ratio greater than 2.0[1]. Actual heart rate was taken by the participant or researcher feeling for the pulse over a 30 second period or by using a pulse oximeter.

Next, the BioGauges system was calibrated according to the low and high values that each person was able to achieve at that moment. Detrending, a process for obtaining a moving average of values, was not incorporated into the BioGauges system because it was important to reduce bias for control. For GSR, participants were asked to relax for a low value and then think of something exciting and raised their temperature for a high value. Participants were asked to devise their own imagery since different things excite different people but to try to vary the images since people habituate over time and what was once exciting is no longer so. For fNIR, participants were asked to think of a non-sensical, droning sound created by repeating "la-la" slowly in their heads for a low value and then to think of counting rapidly but clearly enunciating each number in their heads for a high value. Participants then used this imagery to attempt control of each of the biometric interface technologies according to the protocol provided in Appendix D. Participants were tested with each of the biometric interface technologies in a randomly-ordered session and the trials within each session were also randomly ordered. An objective outcome measure of performance was taken after each trial using the BioGauges methodology and toolset. For this study, performance is the proportion of total trials in which a

[1] All participants except DS38 achieved heartbeat signal-to-noise ratios greater than 2.0. After numerous adjustments of the sensor over a 5-minute period, the system was only able to achieve 1.83 with an accurate heart rate likely due to the overriding strength of the participant's ventilator.

person is able to successfully move a cursor and acquire a bounded target within an allotted timeframe of twenty seconds.

BioGauges measure and characterize the capabilities of a user with a biometric interface technology (A.B. Randolph, McCampbell, Mason, & Moore, 2005; Adriane B. Randolph et al., 2007; Adriane B. Randolph, Melody Moore Jackson et al., 2005). They assess a user's range, reliability, and granularity of control with a biometric interface technology based on very basic tasks. Specifically, *gauges* are very simple control interfaces that reflect changes in biometric phenomenon for the basic components of interaction. Gauges can be used to match a person to a particular biometric interface technology by producing an actual measure of performance (Adriane B. Randolph et al., 2007).

Thus far, gauges have been designed to characterize controllability of discrete and continuous transducers during periods when users intend to control their biometric input (i.e., Control State), such as when they wish to make a selection, and when they do not intend to control it (i.e., No Control State), such as when they are idly looking at the screen reviewing content. The protocols are summarized as follows. The protocols for continuous-output transducers are detailed in Appendix E.

<u>For Discrete Output:</u>

- Response to No Control
- Temporal accuracy to a predictable event
- Response rate to an unpredictable event
- Repetition rate
- Ability to hold and release

For Continuous Output:

- Response to No Control
- Attain output levels (1-D) or point/region in 2-D or 3-D space
- Attain and hold output within a certain range of levels or region in space

This study incorporated a bounded attain task to test spatial control using an fNIR and a GSR-based biometric interface with continuous output. The bounded attain task is illustrated in Figure 13 and shows what the participant saw on his or her computer screen. Figure 14 shows what the researcher saw on her computer screen while monitoring the biometric phenomenon used to control the interface. Here, sample blood oxygenation readings appeared as the blue line at the top of the graph on the operator's screen. The participant was asked to concentrate on the area with the black background and the screen to the left of the black background was used to set up and monitor the tasks. In this study, after the system provided a warning signal a cursor was presented as an orange square that always started in the middle of the screen. The participant attempted to activate the transducer to move the cursor along a one-dimensional track, represented as the blue bar, to attain a target located to the right or left. The target was represented by a yellow rectangle. A new trial started once the participant attained the target by placing the cursor completely within the target boundary lines or the system timed out. The participant had twenty seconds to attempt to attain the target before system timeout.

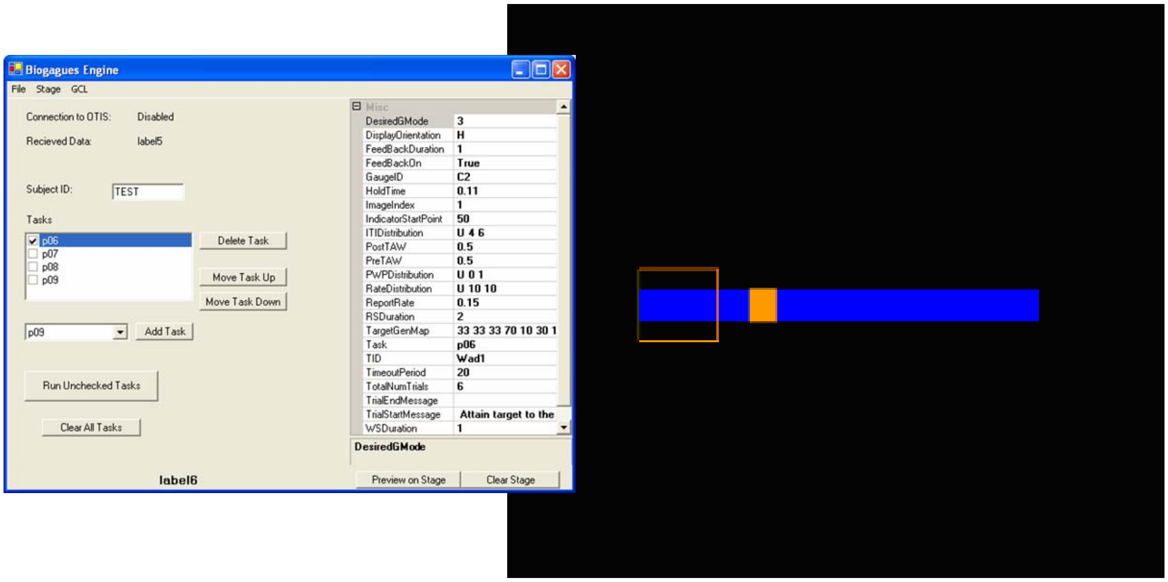

Figure 13. BioGauges interface for the Attain task

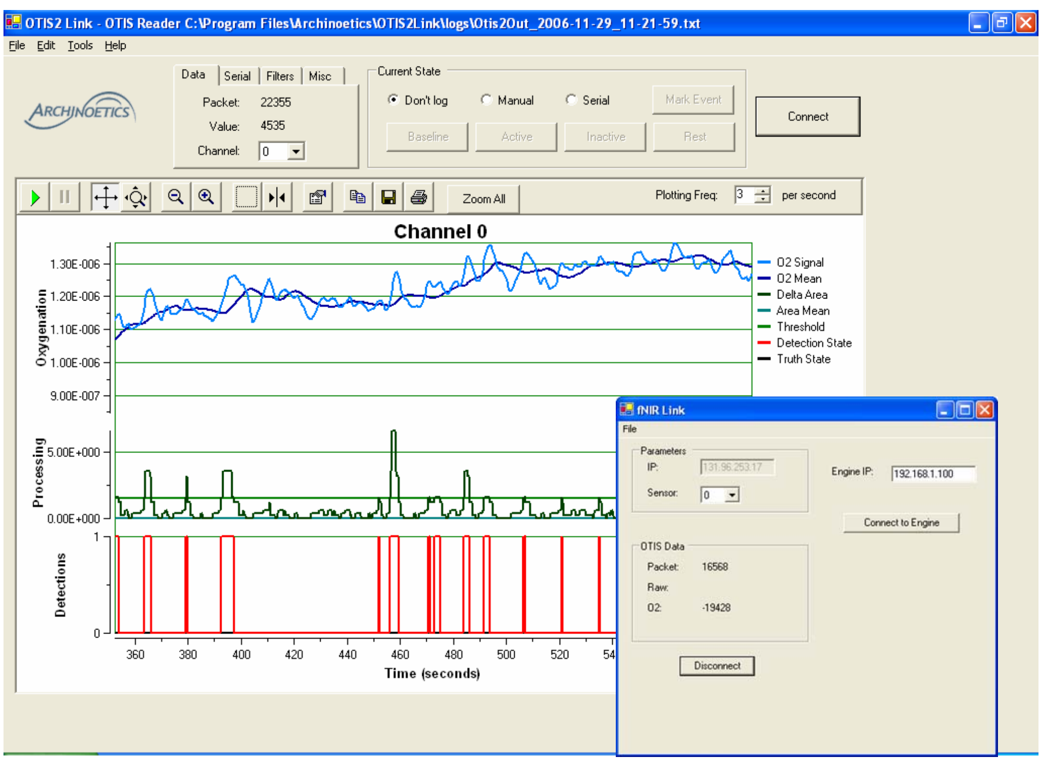

Figure 14. Pucklink interface for use with fNIR biometric interface technology with translating component for BioGauges interface

At the end of the session, each participant then completed an exit questionnaire provided in Appendix F.

4.6. Understanding Individual-Technology Fit

For this exploratory study, performance is the observable evidence of fit between individual characteristics and the fNIR or GSR technology tested. Again, a higher performance indicates a better match and a lower performance indicates a poor match. Table 4 details the predicted exploratory relationships that each individual characteristic will have with performance based on extrapolation from the justifications provided in Table 2. In addition to the fourteen characteristics proposed, seven more characteristics were added upon generation of the biometric user profile questionnaire to take advantage of the opportunity to collect this data from participants. Exploratory relationships were also described for these characteristics and are included below. These hypotheses serve as a theoretical basis for understanding the observed phenomenon within this study.

Table 4. Exploratory relationships of individual characteristics with performance for fNIR and GSR

Category	No.	Dependent Variable	Effect on fNIR Performance	Effect on GSR Performance	Value Set
Demographic Trait	1.	Sex	Males > Females	Males > Females	Categorical (1-male, 0-female), self-reported variable
	2.	Age	Decreases with age	Decreases with age	Continuous, self-reported variable
	3.	Handedness	Right-handers > Left-handers	No effect anticipated	Categorical (1-right, 0-left), self-reported variable
Physiological Trait	4.	Athleticism	Increases as more athletic	Increases as more athletic	Scaled (7-points of athletic identity ranging from 1-sedentary to 7-trained athlete), self-reported variable
	5.	Smoking	Smokers > Non-	Smokers > Non-	Categorical (1-

Category	No.	Dependent Variable	Effect on fNIR Performance	Effect on GSR Performance	Value Set
		Experience	smokers	smokers	yes, 0-no), self-reported variable
	6.	Paralysis	Decreases with increased years of paralysis	Decreases with increased years of paralysis	Continuous (years with paralysis), self-reported variable
	7.	Hair Color	Decreases with darker hair	No effect anticipated	Scaled (1-Blond/None, 2-Brown, 3-Black, 4-Gray), Observed
	8.	Skin Color	Decreases with darker skin pigmentation	No effect anticipated	Scaled (1-White, 2-LightBrown, 3-MediumBrown, 4-DarkBrown), Observed
	9.	Hair Texture	Decreases as hair gets more curly/dense	No effect anticipated	Scaled (1-None, 2-Straight, 3-Curly), Observed
	10.	Affective Drugs	Decreases with use of drugs that affect alertness	Decreases with use of drugs that affect alertness	Categorical (1-yes, 0-no), self-reported variable
	11.	Regular Caffeine Consumption	Increases with regular use of caffeine	Increases with regular use of caffeine	Categorical (1-yes, 0-no), self-reported variable
	12.	Regular Alcohol Consumption	Increases with regular consumption of alcohol	Decreases with regular consumption of alcohol	Categorical (1-yes, 0-no), self-reported variable
	13.	Sustained Head Injury	Decreases with injury	No effect anticipated	Categorical (1-yes, 0-no), self-reported variable
	14.	Hand Dexterity	Increases with dexterity	Increases with dexterity	Categorical (1-yes, 0-no), self-reported variable
	15.	Play(ed) Sports	Increases with sports played	Increases with sports played	Categorical (1-yes, 0-no), self-reported variable
Cognitive Trait	16.	Prior Biometric Training	Increases with more training	Increases with more training	Scaled (Approx. Hours: 0, 2, 7,14), self-reported variable
	17.	Video Game Experience	Increases with more video game experience (may vary for particular types of video games)	Increases with more video game experience (may vary for particular types of video games)	Categorical (1-none, 2-some, 3-extensive), self-reported variable
	18.	Computer Use	No effect anticipated	No effect anticipated	Scaled (1-Hardly Ever, 2-A Little, 3-Extensively), self-reported variable

Category	No.	Dependent Variable	Effect on fNIR Performance	Effect on GSR Performance	Value Set
	19.	Acting Experience	No effect anticipated	Actors > Non-actors	Categorical (1-yes, 0-no), self-reported variable
	20.	Meditation Experience	Meditators > Non-meditators	Meditators < Non-meditators	Categorical (1-yes, 0-no), self-reported variable
	21.	Years of Education	Increases with education	Decreases with education	Continuous, inferred

Further, to more accurately capture video game experience, there were eight types of video games listed that people could play: action/first-person shooter (e.g., Quake), adventure (e.g., Myst), puzzle (e.g., Tetris), real-time strategy (e.g., StarCraft), rhythm (e.g., Dance Dance Revolution), role-playing (e.g., Final Fantasy), simulation (e.g., Gran Turismo), and sports games (e.g., Madden). These eight types of video game experiences increased the total number of variables to twenty-eight. Participants answered questions about video game experience according to the same scale of: none, some, or extensively. A reliability check run across these eight variables assured that the scale was internally consistent for measuring video game experience. The Cronbach's alpha coefficient was .8981 which is greater than the prescribed .7 value indicating that the scale was reliable (Pallant, 2001).

5. Results and Discussion

A quantitative analysis was performed to understand the results of this exploratory study. Thirty-eight participants attempted 5,360 total trials (2,716 fNIR trials and 2,644 GSR trials). Results were aggregated into an overall average success value for each biometric interface technology per person where success is the proportion of successfully completed trials out of trials attempted. Based on the data, both test-wise regression and non-parametric tests were selected as analysis techniques for this study. First, non-parametric testing with Chi-square for independence and Mann-Whitney U revealed if there were any differences between able-bodied and disabled participants. Then, parametric testing with test-wise regression was run to discover which variables had significant impact on performance with each biometric interface technology tested. Spearman Rank Order was used to determine correlations between independent variables. The statistical package, SPSS version 11.0.1, was used to conduct the data analysis.

Convention holds that there should be at least a 5 to 1 ratio for observations to independent variables (Hair, Anderson, Tatham, & Black, 1998) although some believe for social science research that the ratio should be 15 to 1 (Stevens, 1996). Using the minimum rule of thumb for the 28 variables examined, the number of observations should be more than 140. However, as is common with many behavioral science studies and especially common within the BCI literature due to the time-intensive requirements of gathering biometric data, this exploratory study included a relatively small number of people with just 38 sampled. Thus, traditional parametric tests could not be used; experiment-wise regression could not be run using the overall measures of performance, but test-wise regression could be run for each characteristic separately to test for main effects.

In addition, non-parametric tests to discover relationships between characteristics and performance were run. Non-parametric tests are independent of the number of samples involved, are distribution-free, and considered ideal when the data is categorical or scaled (Pallant, 2001). Although considered by some to be less robust than parametric tests, the non-parametric tests of Chi-square for independence, Mann-Whitney U, and Spearman Rank Order, offered suitable alternatives for understanding the study results (Siegel & Castellan, 1988).

5.1. *Descriptive Statistics*

The histograms in Figures 15-21 show the frequency distribution of participants' scores and the normal plots for the continuous and scaled variables: fNIR success, GSR success, age, level of athleticism, years with paralysis, years of education, and hours of training with biometric devices. The histograms in Figures 15-17 show that the data for fNIR Success, GSR Success, and age appear to have been normally distributed. The histograms in Figures 18, 19, and 21 show that the data for level of athleticism, years with paralysis, and hours of biometric training were positively skewed, where most participants reported lower values. The histogram in Figure 20 shows that the data for Years of Education was negatively skewed, where most participants had undergraduate degrees and some graduate work.

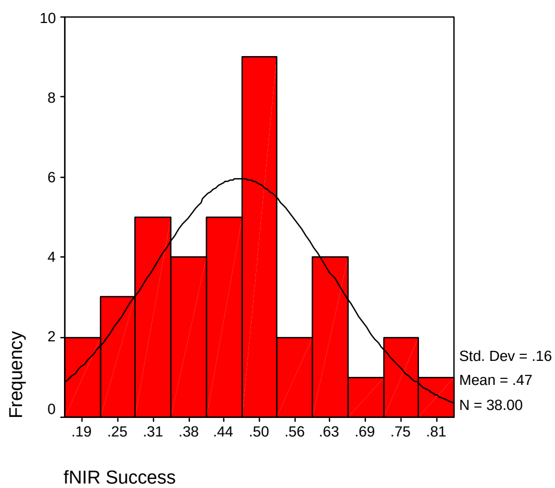

Figure 15. Histogram of fNIR Success

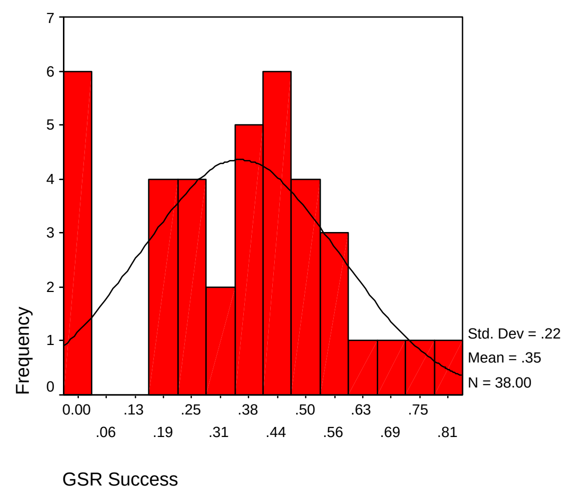

Figure 16. Histogram of GSR Success

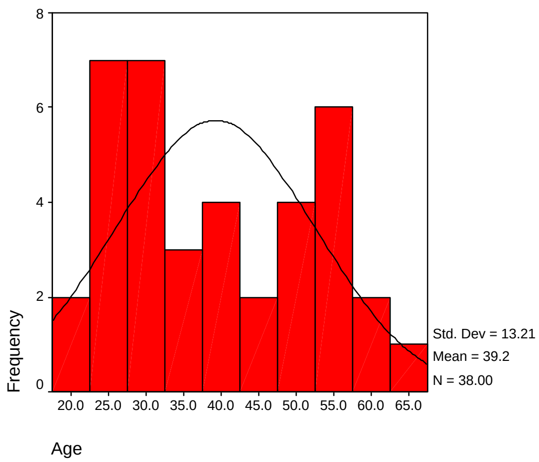

Figure 17. Histogram of Age

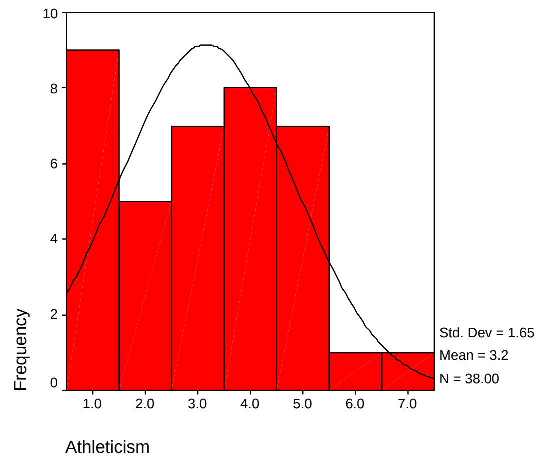

Figure 18. Histogram of Level of Athleticism

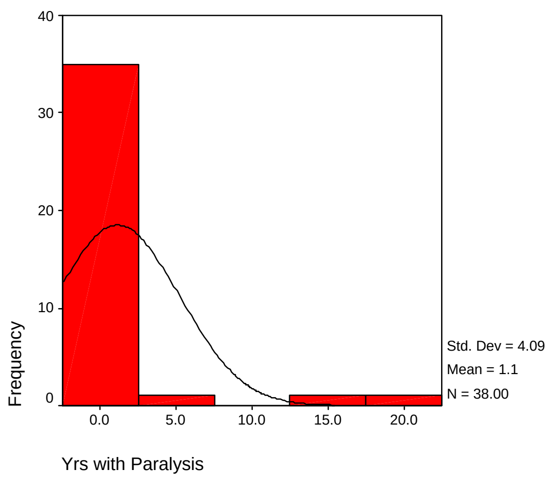

Figure 19. Histogram of Years with Paralysis

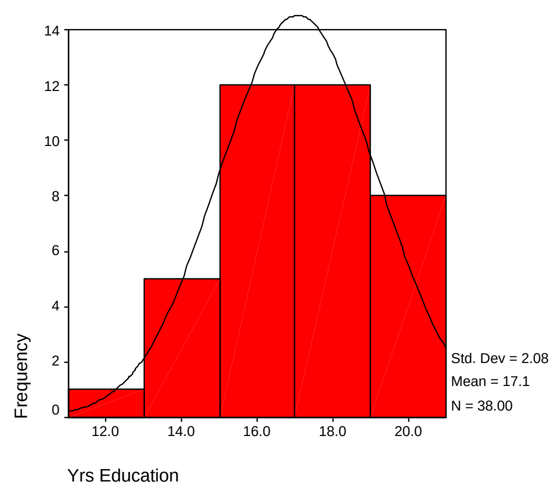

Figure 20. Histogram of Years of Education

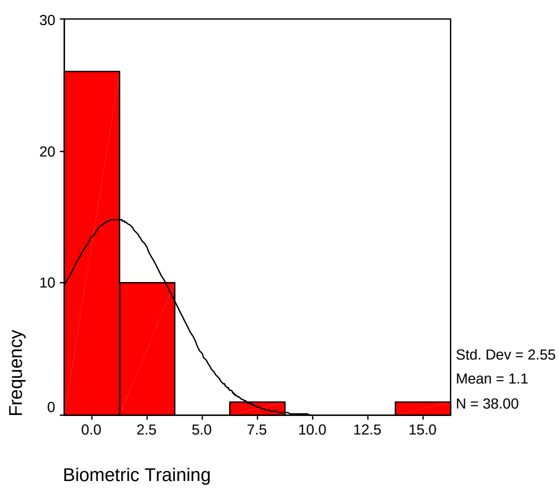

Figure 21. Histogram of Hours of Biometric Training

Table 5 shows results of tests for normality where a significance value (Sig.) greater than .05 indicates normality. Table 5 also shows the obtained value (Statistic) and the Degrees of Freedom (df) according to the sample size. A Shapiro-Wilk Test for normality is generally used when sample sizes are less than 2000 (Shapiro & Francia, 1965). Although the dependent variables of performance are normally distributed, the independent variables are not – including age, which appeared to be normally-distributed from visual inspection. This does not indicate a problem with the scale but rather reflects the underlying nature of the phenomenon being measured. Although the independent variables were not all normally distributed as generally assumed by regression, regression analysis is robust enough to handle such departures and data transformation techniques are rife with controversy (Pedhazur, 1997). Therefore, the data were not transformed.

Table 5. Test for normality

Tests of Normality

	Shapiro-Wilk		
	Statistic	df	Sig.
fNIR Success	.980	38	.709
GSR Success	.963	38	.231
Age	.929	38	.018
Athleticism	.918	38	.008
Biometric Training	.452	38	.000
Yrs with Paralysis	.304	38	.000
Yrs Education	.909	38	.004

A summary of descriptive statistics is provided in Table 6. Table 6 shows the sample size (N), the Minimum and Maximum values obtained, the average value (Mean), and the Standard Deviation which indicates the dispersion of the sample. Detailed descriptive statistics for the continuous/scaled variables and frequencies for the categorical variables are provided in

Appendix G. Only one person responded “yes” to having sustained a head injury so this variable was thrown out from analysis due to lack of variation. The variable for handedness was also thrown out because there were only four people who displayed this characteristic and five was needed as the minimum for comparative statistical analysis. This reduced the number of variables analyzed to twenty-six.

Table 6. Summary of descriptive statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
fNIR Success	38	.181	.833	.46637	.158585
GSR Success	38	.000	.806	.35435	.217120
Age	38	21	67	39.24	13.206
Athleticism	38	1	7	3.16	1.653
Yrs with Paralysis	38	0	19	1.13	4.088
Yrs Education	38	12	20	17.08	2.084
Biometric Training	38	0	14	1.08	2.551
Valid N (listwise)	38				

The chance of hitting the desired target was 1 / 7 = .143 because although there were four possible targets, there were five bins including the center bin where the cursor always started and then two infinite edges totaling seven possible results for cursor placement. As Table 6 shows, the average fNIR success was .466 and the average success for GSR was .354 (detailed results of participants’ performance with fNIR and GSR may be seen in Appendices H and I). Because these average success values were significantly greater than chance at a 95% confidence level, on average, people were able to control both the fNIR and GSR technologies; the success values needed to be greater than .330 to be considered significantly greater than chance (Pearson NCS, 2006). Twenty-eight participants (74 percent) were able to achieve greater than chance results with fNIR, where the minimum fNIR success was .181 and the maximum fNIR success was .833. For GSR, 23 participants (60 percent) were able to achieve greater than chance results, where there were individuals who were unable to generate a response with the GSR device at all for calibration and hence their success was .000 and some achieved as high as .806. For those individuals unable to generate a response with GSR, in each case, the researcher verified that the sensors were in fact operating properly and able to record variations in GSR by placing the sensors on her own fingers and observing fluctuations in values. In general, these individuals reported that they did not consider themselves to be very “sweaty”.

5.2. Population Differences

After initial exploration of the data, the file was split between able-bodied and disabled persons to understand if any differences existed between groups. If significant differences were found, then it meant that the characteristics of able-bodied people were not good surrogates for those people with ALS and the data would be analyzed per group instead of as a whole. A variable “ALS” represented the presence of the chronic disease ALS with a 0 for “no” and a 1 for “yes” per person. The sample included at least five people with ALS to satisfy minimum criteria for running between-group, non-parametric tests (Pallant, 2001). Individuals varied in the progression of the disease where participant DS22 still had upper body movement but used a wheelchair and participant DS38 was almost completely locked-in except for a slight, controlled flick of the wrist.

A Chi-square test for independence determined if differences existed between the categorical characteristics of able-bodied participants and the categorical characteristics of those participants with ALS. A Pearson Chi-Square value with significance greater than .05 indicated that there did not appear to be a difference between populations for that characteristic. A Mann-Whitney U test determined if differences existed between the continuous/scaled characteristics of able-bodied participants and the continuous/scaled characteristics of those participants with ALS. A

Z value with an exact significance greater than .05 indicated that there did not appear to be a difference between populations for that characteristic. Detailed results of both tests may be reviewed in Appendix J. Table 7 presents a summary of the Chi-Square and Mann-Whitney U tests for differences between able-bodied and disabled participants. Two asterisks indicate which values significantly differed across groups at the level of $p \leq .05$.

Table 7. Summary of results of tests for differences between able-bodied and disabled participants

Variable	**Z-value/Pearson Chi-Square Value**	***p*-value**
Technology Ran First	2.073	.150
fNIR Success	-.368	.738
GSR Success	-1.363	.187
Sex	.086	.770
Age	-1.427	.159
Athleticism	-2.288	.021**
Smoking Experience	2.056	.152
Paralysis	-6.064	*p* < .001**
Hair Color	6.855	.077
Skin Color	2.695	.441
Hair Texture	1.085	.581
Affective Drugs	14.528	*p* < .001**
Regular Caffeine Consumption	2.699	.100
Regular Alcohol Consumption	2.657	.103
Hand Dexterity	.001	.979
Play(ed) Sports	.010	.922
Prior Biometric Training	-.663	.615
First-Person Shooter Games	3.573	.168
Adventure Games	2.159	.340
Puzzle Games	.359	.836
Strategy Games	1.303	.521
Rhythm Games	2.056	.358
Role-Playing Games	3.359	.187
Simulation Games	2.795	.247
Sports Games	.722	.697
Computer Use	7.206	.027**
Acting Experience	.494	.482
Meditation Experience	25.498	*p* < .001**
Years of Education	-.941	.376

The results show that there was a significant difference in values (where $p \leq .05$) between able-bodied and disabled participants for only five of the twenty-six total characteristics (less than 20 percent): use of affective drugs, meditation experience, computer use, level of athleticism, and years with paralysis. In addition, a Chi-square test indicated that the order in which the biometric interface technology was presented to participants did not matter to the results because the Pearson Chi-Square *p*-value was .150.

A significant difference in means was anticipated for the paralysis and athleticism variables because of the general limited mobility of people who have ALS and both variables assessed current states. There was a difference in means of 8.60 between able-bodied and disabled participants for paralysis which was significant at the $p \leq .001$ level. There was a difference in means of 1.79 between able-bodied and disabled participants for athleticism which was significant at the $p = .021$ level. Both variables represented current states of motor ability whereas the variable for play(ed) sports represented the person's previous athletic ability for those individuals with paralysis. Therefore, it made sense that the difference in the proportion of people who play(ed) sports to those who do/did not play sports between able-bodied participants (63.6%) and disabled participants (60.0%) was not observed to be significantly different with $p = .922$.

Further, ALS patients are often prescribed a cocktail of drugs to assist their immune systems and various other needs; these drugs often affect alertness levels, so the difference in proportion of people who did take affective drugs to those who did not take affective drugs between able-bodied participants (-81.8%) and disabled participants (60%) was expected to be significant ($p \leq .001$).

The statistically significant differences observed in overall frequency of computer use between able-bodied participants (75.8%) and disabled participants (20%) at the $p = .027$ level may be due to some remaining confound with the survey question. Although mobility may be distinctly limited for ALS patients and they may have responded that they engaged in little to no computer use, the person may have previously used computers extensively and thus still been very computer literate; this is the crux of the computer use variable.

There was no variation for meditation experience for ALS patients; they all reported that they engaged in regular meditation which is perhaps a necessary coping mechanism when locked-in, thus explaining the significant difference observed in the proportion of meditators to non-meditators between able-bodied participants (-87.8%) and disabled participants (100%) at the $p \leq .001$ level. In addition, a Mann-Whitney U test revealed that there was no significant difference observed between the mean fNIR and GSR success values for able-bodied participants (difference in means of .03012) and disabled participants (difference in means of .1825) because the *p*-values were .738 and .187 respectively.

Overall, the differences in these few characteristics were not compelling enough to indicate gross differences between the populations nor did these differences seem to affect performance as the following results explain. Therefore, these results suggest that able-bodied individuals were able to serve as surrogates for disabled persons in studies involving fNIR and GSR input. This formal comparison between able-bodied and disabled persons had not previously been examined in the field and represents a significant contribution that helps justify testing biometric interfaces with able-bodied individuals prior to testing with ALS patients.

5.3. Test-Wise Regression

Because no overall difference was observed between able-bodied and disabled participants, the data were able to be combined for further analysis of participants' results. Test-wise regression was performed with each individual characteristic and fNIR success and then again with GSR success. Table 8 provides a summary of the twenty-six regressions for both technologies listed per individual characteristic, whereas Appendix K provides the detailed regression results. Table 8 shows the R-square value which tells how much variance in success is explained by the characteristic, the Beta coefficient is reported because this is a standardized value that allows cross-comparisons between coefficient values independent of scale, and the *p*-value is the significance level. The individual characteristics that appear to have a significant relationship with performance (*p*-value ≤ .05) are indicated with two asterisks; the characteristics that are significant at the *p*-value ≤ .10 are indicated with one asterisk.

Table 8. Summary of test-wise regression results

Individual Characteristic	fNIR R^2 Value	fNIR Beta	fNIR *p*-value	GSR R^2 Value	GSR Beta	GSR *p*-value
Sex	.063	.251	.128	.176	.420	.009**
Age	.208	-.456	.004**	.253	-.503	.001**
Athleticism	.009	.093	.578	.017	.131	.434
Smoking Experience	.001	-.031	.855	.000	-.012	.942
Paralysis	.000	.005	.976	.023	-.151	.356
Hair Color	.005	-.074	.659	.134	-.367	.024**
Skin Color	.002	-.043	.797	.149	-.386	.017**
Hair Texture	.070	.264	.109	.131	-.362	.026**
Affective Drugs	.024	-.154	.356	.041	-.203	.222
Regular Caffeine Consumption	.127	-.356	.028**	.003	.057	.734
Regular Alcohol Consumption	.009	-.093	.580	.126	.355	.029**
Hand Dexterity	.003	.058	.728	.057	.238	.150
Play(ed) Sports	.009	.097	.564	.066	.258	.118
Prior Biometric Training	.029	.171	.305	.009	-.096	.565
First-Person Shooter Games	.062	.249	.132	.117	.342	.035**
Adventure Games	.057	.239	.149	.027	.163	.327
Puzzle Games	.046	.213	.198	.032	.178	.285
Strategy Games	.023	.152	.363	.178	.422	.008**
Rhythm Games	.030	.174	.297	.008	.089	.595
Role-Playing Games	.050	.224	.177	.205	.453	.004**
Simulation Games	.043	.206	.214	.135	.368	.023**
Sports Games	.049	.221	.183	.095	.308	.060*
Computer Use	.014	.120	.474	.021	.146	.382
Acting Experience	.013	.115	.492	.066	-.256	.120
Meditation Experience	.002	-.040	.813	.218	-.467	.003**
Years of Education	.124	.352	.030**	.001	-.030	.858

For fNIR, there are three individual characteristics that appear to have a significant relationship with performance at *p*-value ≤ .05. These characteristics should be highly considered when deciding if a person is a good candidate for an fNIR device and are explained as follows.

1. *Age* – There is a negative correlation with age which indicates that younger people have better success than older people controlling an fNIR device. This falls in line with the original exploratory relationship that localized blood flow decreases with age and may explain this phenomenon.
2. *Regular Caffeine Consumption* – There is a negative correlation which indicates that non-caffeine consumers have better control of an fNIR device. This result is contrary to the exploratory relationships that regular caffeine consumption has a positive effect on performance.
3. *Years of Education* – There is a positive correlation which indicates that as people spend more time in school, their control of an fNIR device increases, and this supports the original exploratory relationship.

Interestingly, hair color, skin color, and hair texture do not appear to have strongly significant relationships with fNIR performance although hair texture has a marginally significant relationship. These characteristics were thought to be among the more influential variables per anecdotal evidence from collaborators, but this study indicates that this is not the case. No definitive statements can be made regarding a relationship with handedness because there were only four people who were left-handers which precludes inter-group comparison because a minimum of five is needed. Further, characteristics related to physical abilities and sex also appear not to have a relationship with performance. This is encouraging for use of this technology by locked-in patients; because there does not appear to be a dependency on physical or motor ability for control. So, as a person progresses with ALS, he or she should be able to continue utilizing an fNIR device although there appear to be tradeoffs as age increases.

For GSR, there are twelve individual characteristics that appear to have a significant relationship with performance at *p*-value $\leq .05$ and are as follows. These characteristics may be condensed into six variables and should be highly considered when deciding if a person is a good candidate for being able to control a GSR device.

1. *Age* – There is a negative correlation with age which indicates that younger people have better success than older people with controlling a GSR device. This falls in line with the original exploratory relationship that circulation slows with age affecting emission and absorption of sweat.
2. *Sex* – There is a positive correlation with sex indicating that men perform better than women at controlling GSR. This result supports the proposed exploratory relationship about men sweating more than women and thus a better range of control.
3. *Regular Alcohol Consumption* – Regular alcohol consumption is positively correlated with GSR performance perhaps reflecting that alcohol promotes thinner blood and thus increases blood flow.
4. *Meditation* – Meditation is negatively correlated with performance indicating that people who do not meditate regularly perform better controlling GSR. This supports the original exploratory relationship, perhaps indicating that people who meditate are calmer and have difficulty raising their excitement level, thus making control of a GSR device more difficult.

5.-9. *FPS, Strategy, Role-Playing, Simulation, and Sports games* – These game types all positively correlate with performance. Further, these game types highly correlate with each other as shown in Appendix L. An average of these values representing overall video game experience appears to be better to avoid multicollinearity issues in the future.

10.-12. *Skin color, Hair color, Hair texture* – Contrary to the exploratory relationship, these individual characteristics all negatively correlate with performance indicating that as features lighten, performance increases. These characteristics all highly correlate with each other as shown in Appendix L, and it is plausible that this correlation is a reflection of race. By using hair color as the surrogate, the same positive relationship is reflected. Further investigation into related physiological literature uncovered that conductivity varies with race, where people with brown skin have higher conductivity than people with white skin (Berardesca & Maibach, 2003). This higher conductivity may result in saturation of the sensors given the set signal range for the Lafayette Instrument GSR system of +/- 10V.

5.4. Summary of Results

Overall, from the experience of running thirty-eight participants with fNIR and GSR biometric interface technologies, it appears that there are significant relationships between different individual characteristics and performance. The only shared result between fNIR and GSR performance is the significantly observed inverse relationship with age for both. Age has the largest Beta coefficient (-.456 for fNIR and -.503 for GSR) and R-Square (.208 for fNIR and .253 for GSR) values for both technologies indicating that age has the largest weight and explains the most variance of success with fNIR and GSR. Therefore, age should be given the most consideration when considering a person's match with *either* fNIR or GSR technologies because it appears that younger people have a better chance at success with both. To achieve success that is significantly better than chance of .330, the person should be 65 years or younger for fNIR and 43 years or younger for GSR; this pivot point was calculated by taking the unstandardized coefficient (B_1) for fNIR (-5.47×10^{-3}) and for GSR (-8.27×10^{-3}) and solving for X_1 using the equation: $y = B_0 + B_1X_1$, where y (dependent variable) was .330 and B_0 (Constant) was .681 for fNIR and .679 for GSR. The unstandardized coefficient and constant values may be found for all characteristics in Appendix K.

In addition to younger age, increased success with fNIR appears to be related to non-regular caffeine consumption and increased years of education. To achieve success that is significantly better than chance of .330, the person should have 12 years or more of education calculated using a similar process to that for calculating the pivot point for age. Success with GSR appears to increase for men, regular alcohol consumption, non-practice of meditation, increased video game experience, and people with lighter hair colors. To achieve success that is significantly better than chance of .330, the person should have hair that is lighter than black (2.76) calculated using a similar process to that for calculating the pivot point for age. These characteristics may be captured using a biometric user profile.

Once captured within a biometric user profile, to determine a person's ITF with a similar fNIR or GSR technology a checklist such as the biometric technology checklist provided in Table 9 may be used. A *biometric technology checklist* lays out all of the discovered relationships with performance for individual characteristics with a particular biometric interface technology. In the table, a check or "x" indicate if ITF is present or not for the technology with the particular characteristic expressed, and shading indicates that the characteristic has no observed significant relationship with the technology.

Table 9. Biometric Technology Checklist for fNIR and GSR technologies

No.	Individual Characteristic	fNIR-ITF	GSR-ITF
1.	The person is under the age of 43	✓	✓
2.	The person is of age 43 to 64	✓	x
3.	The person is 65 years or older	x	x
4.	The person is a male		✓
5.	The person is a female		x
6.	The person does not regularly consume caffeine	✓	
7.	The person does regularly consume caffeine	x	
8.	The person completed high school	✓	
9.	The person did not complete high school	x	
10.	The person does not regularly meditate		✓
11.	The person does regularly meditate		x
12.	The person plays/played video games		✓
13.	The person does/did not play video games		x
14.	The person regularly drinks alcohol		✓
15.	The person does not regularly drink alcohol		x
16.	The person has brown hair or lighter or no hair		✓
17.	The person has black hair		x

Ideally, the person would have 3 checks for fNIR-ITF and 6 checks for GSR-ITF, representing an ideal fit profile for each biometric interface technology. A recommended heuristic may be to have at least 2 out of 3 matches to have an overall good ITF with fNIR and 5 out of 6 matches to have a good ITF with GSR. Unfortunately, aside from a person being of age 43 to 64, no other characteristics were discovered to have a significant relationship with performance that would help to decide *between* fNIR and GSR technologies because there are no other overlapping results with differing effects. For example when considering the person's sex, if the person is female, GSR may not be considered to be a well-matched technology but no statement may be made about if fNIR would instead by a good match because sex was not observed to have a relationship with fNIR success.

6. Conclusions

This work followed an exploratory design research approach by creating a new framework and methodology for matching individual characteristics with biometric interface technology features. It proposed several characteristics of individuals to examine based on a review of related literature on biometric interfaces and human physiology and ongoing research with colleagues in the field of biometric interfaces. Biometric user profiling appears to be a helpful methodology to explain an individual's performance with fNIR or GSR technologies by capturing his or her biometric user profile and considering practical tradeoffs between the matches on particular characteristics to determine an overall ITF. The steps of the biometric user profiling methodology are shown in Figure 22.

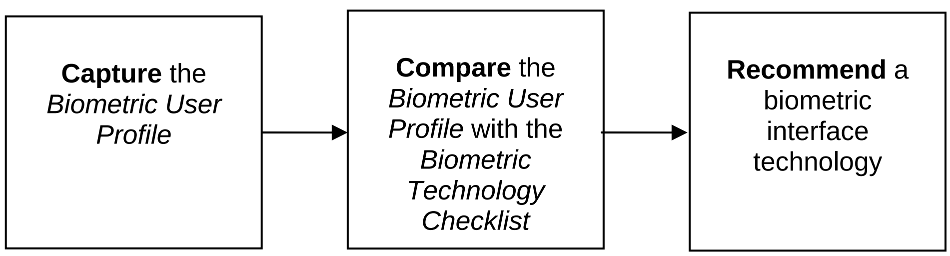

Figure 22. Biometric User Profiling Methodology

An assistive technology practitioner may use a questionnaire that asks about the person's age, sex, regular caffeine consumption, experience playing video games, years of education, and meditation experience, and then observe hair color. This would be a relatively short process with only seven questions to ask the person.   The eight total data points would then be compared against a checklist to determine overall ITF. For fNIR, a younger adult who has gone on to college and does not regularly consume caffeine should perform best. For GSR, a blond, younger adult male who does not regularly meditate but does have extensive experience playing video games and regularly consumes alcohol should perform best. These serve as ideal biometric user profiles for fNIR and GSR.

This work provides encouragement for more research to further understand the differences between individuals and the impacts on biometric interface design. The following sections provide a summary of contributions provided by related work as part of a multi-paper dissertation, overall conclusions from this study, limitations of the study, and intended follow-on work.

6.1. Summary of Research Contributions

This section summarizes the individual research contributions that were captured as six papers through the dissertation study. Table 10 lists the publication details for each paper and the associated research questions they addressed. The following subsections present the contributions of each paper according to the topic that was covered.

Table 10. Summary of related research papers

No.	Title	Authorship	Publication Outlet	Approach	Research Question
1	Context Aware Communication for Severely Disabled Users	**Davis (Randolph), Adriane B.**, Moore, Melody M., and Storey, Veda C.	**Proceedings** of the *Conference on Universal Usability (CUU) 2003*, Vancouver, B. C. Canada, November 10-11, 2003	Case study	RQ1
2	Deriving User Profiles for Augmentative Communication	Moore, Melody M., Storey, Veda C., **Davis (Randolph), Adriane B.**, and Napier, Nannette	**Proceedings** of the *Americas Conference on Information Systems (AMCIS)*, New York City, NY, August 6-8, 2004	Interviews Observations Questionnaires	RQ1
3	User Profiles for Facilitating Conversations with Locked-in Users	Moore, Melody M., Storey, Veda C., **Randolph, Adriane B.**	**Proceedings** of the *International Conference on Information Systems (ICIS)*, Las Vegas, NV, December 10-14, 2005	Prototype Empirical test Questionnaires	RQ1

No.	Title	Authorship	Publication Outlet	Approach	Research Question
4	Controllability of Galvanic Skin Response	**Randolph, Adriane B.**, McCampbell, Luke A., Moore, Melody M., and Mason, Steven G.	**Proceedings** of the *International Conference on Human-Computer Interaction (HCII)*, Las Vegas, NV, July 22-27, 2005	Case study Empirical test	RQ2
5	BioGauges: Toward More Objective Evaluation of Biometric Interfaces	**Randolph, Adriane B.,** Moore Jackson, Melody, and Mason, Steven G.	**Targeting** journal publication in *ACM Transactions on Computer-Human Interaction*	Case study Empirical test	RQ2, RQ3
6	Toward Predicting Control of a Brain-Computer Interface	**Randolph, Adriane B.,** Karmakar, Saurav, Moore Jackson, Melody	**Proceedings** of the *International Conference on Information Systems (ICIS)*, Milwaukee, WI, December 10-13, 2006	Empirical test	RQ3

Figure 23 provides a conceptual map of the topics covered by the research papers associated with this dissertation work.

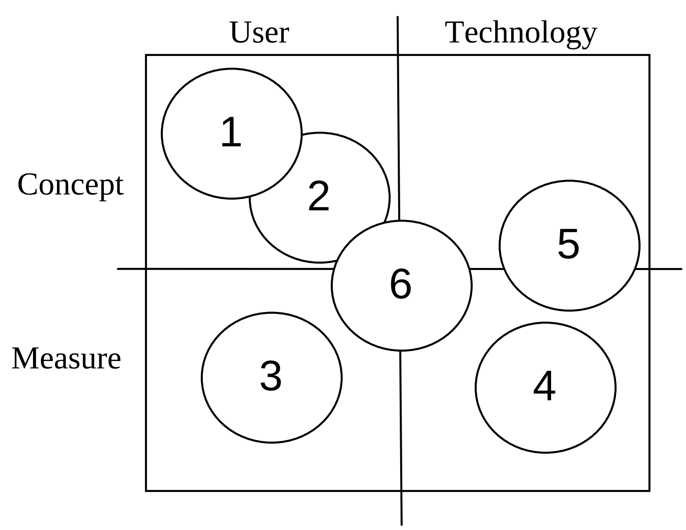

Figure 23. Map of related research papers and coverage

6.1.1. Biometric User Profiling

Paper 1: Context Aware Communication for Severely Disabled Users

Even with assistive communication technology, interactive conversation is extremely difficult for users with severely limited mobility and loss of speech. Input to such devices is painfully slow and subject to high error resulting in output that may not reflect the true intentions of the user. Conversational prediction, such as word completion, has been incorporated into assistive systems to help speed up communication but can be further improved by considering the contextual interaction between the user and conversant. Contextual information applied to user profiles can greatly enhance conversational prediction and increase a severely disabled user's control over his or her complex world. For example, information about a particular nurse being in a patient's room may spark conversational topics unique to that relationship such as about the patient's comfort or care.

This paper presents a framework that integrates a rich profile of the user, a model of the user's environment, and actors on that environment. To test the validity of the framework, a set of profiles was developed and applied in two different scenarios. Initial results showed that the context-aware user profiles could increase both the accuracy and speed of the communication. This work serves as the first step towards developing biometric user profiles.

Paper 2: Deriving User Profiles for Augmentative Communication

User profiling provides personalized and relevant content for users of information technology. Describing and representing an individual's capabilities and interests can enhance assistive technology for users with severe disabilities, such as paralysis and the inability to speak. These users are particularly challenged when attempting to interface with technology because of their limited means for providing input. This paper describes the extent to which user profiling can be helpful for encapsulating the preferences of such disabled users. It also presents a methodology for capturing and representing user profile information in augmentative and assistive communication devices. User profiles were developed for both disabled users and their conversational partners.

Paper 3: User Profiles for Facilitating Conversations with Locked-in Users

This research presents an approach to developing user profiles for locked-in users. The profiles can be used to enhance the speed and accuracy of conversation by reducing the selection space for conversational topics. An empirical study that simulated the application of user profiles demonstrated how they could be used to improve the speed and accuracy of conversation in severely disabled users relying on augmentative and assistive communication devices.

6.1.2. Objective Measurement of Biometric User Control

Paper 4: Controllability of Galvanic Skin Response

Biometric interfaces are on the leading edge of the assistive technology and human-computer interaction fields. When a user's motor disability prevents input from traditional physical input devices, alternatives that do not require muscle movement must be considered. Galvanic Skin Response is one such method for control that does not require muscle-based input but rather relies on biofeedback. Work at the Georgia State University BrainLab has included examination of GSR as a viable input mechanism for communication and control for users with severe motor disabilities such as ALS. This paper details a study with 5 able-bodied participants to determine the basic characteristics of control using GSR and the BioGauges toolset.

Paper 5: BioGauges: Toward More Objective Evaluation of Biometric Interfaces

Biometric interfaces measure small changes in a user's psychophysiological properties to provide alternative paths for controlling computers and other devices. The motivation for developing biometric interfaces has been to offer channels of control to people with severe physical disabilities. Although research and development of these interfaces has progressed substantially in recent years, it has been difficult to objectively compare user performance with different biometric interfaces to determine the optimum choice for a particular person. The BioGauges method and toolset provide a mechanism to fully characterize the outputs of a user operating a biometric interface to determine the range, reliability, and granularity of control possible. This paper first demonstrates the method with a study of ten able-bodied people characterizing two different continuous biometric interfaces with a thresholded task. Then, this paper further demonstrates the method by assessing the spatial granularity of two continuous biometric interfaces for seven able-bodied people and three people with varying stages of ALS.

6.1.3. Explaining Performance with Biometric Interface Technologies

Paper 6: Toward Predicting Control of a Brain-Computer Interface

There is currently no formalized process for determining a user's aptitude for control of various biometric interfaces without testing on an actual system. This study presents how basic information captured about users may be used to predict their control of a brain-computer interface that is based on electrical variations in the motor cortex region of the brain measured by EEG. Based on data from 55 able-bodied users, this study found that the interaction of age and daily average amount of hand-and-arm movement by individuals correlates to their ability in brain-computer interface control. This research serves as a proof-of-concept for a more robust model linking individual characteristics and control of various biometric interfaces.

6.1.4. Overall Contributions

This work advances knowledge in the field of human-computer interaction by examining more closely relationships within biometric interfaces and assistive technology systems. This work is an important step toward better matching users with appropriate biometric interface technologies according to their characteristics, thus saving time and resources expended. Although thirty-eight participants may sound small, this is the most extensive study to date exploring fNIR and GSR devices for control purposes. A significant finding is that able-bodied participants may in fact be suitable surrogates for studying applications that target people with motor disabilities. This was shown to be true for fNIR and GSR research and may hold true for other types of biometric interface technologies, as well. In the field of MIS, this work expands upon the concepts of technology fit and validates aspects of Goodhue's popular model for TTF in a new context for biometric interface technologies with stronger results by measuring actual performance rather than perceptions. Finally, this work emphasizes the power of user-centered design by providing a better understanding of individual user characteristics as they relate to biometric interface technologies which should help stimulate better design of biometric interface systems.

6.2. Limitations and Future Research

There were some limitations to this study related to the survey tool and performance metrics. More work could be done to further refine the questions in the biometric user profiling questionnaire to elicit more precise responses. Instead of categorical yes/no responses, a scaled response could be used for questions inquiring about regularity of behavior, such as consuming caffeinated items, using a computer (in the past or present), engaging in meditation, and drinking alcohol. For example, without a scale the question about regular alcohol consumption may have been interpreted more widely than intended; some participants may have considered themselves to regularly drink alcohol if they consumed a drink each weekend whereas some may have consumed a drink multiple times in a day. Although this question was not attempting to reveal alcoholism, there may be related physiological implications to consider for people classified as alcoholics versus "social drinkers".

For performance metrics, participants attempted a difficult task to attain a bounded target instead of simply activating the transducer above or below a certain threshold to attain an infinitely large target area. Performance should increase significantly with a thresholded task. Further, although detrending was not used in this study, participants should benefit from use of an interface that dynamically calibrates because sometimes peoples' ranges shifted over the course of one task. However, this study was not focused on understanding the interface designed, but rather on understanding the underlying relationships of individual characteristics with control.

Further examination of individual characteristics and the potential differences between able-bodied and disabled participants' motivation and frustration levels is still necessary. Also, a larger sample size would allow stronger conjectures by using parametric statistics for data analysis. Unfortunately, achieving a larger sampling of disabled participants poses a definite challenge. According to members of the ALS Association, although approximately 30,000 ALS patients reside in the United States many of them are unaware of support networks available and do not have a technically-savvy team to help connect them with resources. Therefore, it may be necessary to recruit participants with illnesses and conditions other than ALS that result in motor disabilities. In addition, further investigation into the effects of handedness on performance may prove interesting because of differences in cognitive development.

This study focused on initial control but does not specifically address the potential long term effects of training with biometric interface technologies on performance. It may be possible that training could supersede characteristics from a person's biometric user profile. A longitudinal, controlled study is needed to isolate the effects of training on performance with particular biometric interface technologies. In particular, a fully-crossed (2 x 2) free experiment could be run to compare people who are predicted to fit either a fNIR or GSR biometric interface technology with those who are predicted not to fit and people in both of these groups who have received training with those who have not. Able-bodied participants may be used to obtain a larger sample size.

Although tested with a select set of biometric interface technologies, we may expand this methodology to explain other types of continuous input technology, such as some EEG-based recordings, and the effect of task on performance. In the future, this work may be extended to technologies with discrete types of transducer output, tested under different conditions, resulting in a more widely validated model that may be used for prediction of performance. Although not addressed here, future work could explore the temporary effects of drugs and caffeine on performance or differences in environments that impose temporary disabilities. In addition to testing with different biometric interface technologies, different tasks may be analyzed for their effect on performance. Only one task was investigated here, but a study to replicate and extend this work may reveal a deeper cognitive relationship between the task and the type of biometric interface technology.

This work may be extended into a protocol for conducting integrated remote assessments for users of biometric interface technologies. Results of this dissertation work may serve as screening and analysis portions of a protocol which can be shared across remote teams to determine what system works best for a user. However, because an integrated approach for remote team collaboration would likely require a form of high-computing infrastructure such as grid-technology and deeper investigation into related telemedicine techniques, this is presently outside the scope of a dissertation but may be appropriate for career work.

Finally, opportunities exist for future collaborations with governmental organizations, such as the Air Force, to understand if biometric interface technologies like fNIR and GSR may be used in conditions with extreme forces that affect vascular activity. Performance may be compared for fNIR, GSR, and EEG devices, where EEG has previously been investigated for use by jet pilots. This represents just one of many directions for future research as a result of this work.

7. Appendices

Appendix A: Participant Details

Participant ID	Age	Sex	Smoke	Yrs Quit	Drugs	Alertness	Caffeine	Alcohol	Head Injury	Act	Meditate	Dexterity	Sports	Athleticism
DS01	32	M	N	N/A	N	N/A	N	Y	N	N	N	Y	Y	2
DS02	55	M	Y	0	N	N/A	Y	N	N	N	N	Y	Y	6
DS03	56	F	N	N/A	N	N/A	Y	N	N	N	N	Y	Y	2
DS04	54	M	N	N/A	N	N/A	N	Y	N	N	N	N	Y	4
DS05	53	F	Y	2	Y	less	Y	N	N	N	N	Y	Y	1
DS06	56	M	Y	35	N	N/A	Y	Y	N	N	N	Y	N	1
DS07	51	F	N	N/A	N	N/A	Y	N	N	N	N	Y	Y	1
DS08	52	M	Y	16	N	N/A	Y	N	N	N	N	Y	Y	1
DS09	59	F	N	N/A	N	N/A	N	N	N	N	Y	N	Y	2
DS10	23	M	N	N/A	N	N/A	N	N	N	N	N	N	Y	7
DS11	59	F	Y	30	N	N/A	Y	N	N	N	N	N	Y	2
DS12	48	F	N	N/A	Y	more	Y	N	N	N	N	N	N	4
DS13	39	M	Y	0	N	N/A	Y	N	N	N	N	N	Y	2
DS14	30	M	N	N/A	N	N/A	Y	N	N	N	N	N	Y	4
DS15	40	M	N	N/A	N	N/A	Y	N	N	N	N	N	Y	5
DS16	34	F	N	N/A	N	N/A	Y	N	N	N	N	N	N	3
DS17	38	F	Y	3	N	N/A	Y	N	N	Y	Y	Y	N	3
DS18	30	M	N	N/A	N	N/A	N	N	N	N	N	Y	Y	5
DS19	30	M	N	N/A	N	N/A	N	N	Y	N	N	Y	Y	3
DS20	29	F	N	N/A	N	N/A	N	Y	N	N	N	Y	Y	5
DS21	37	M	N	N/A	N	N/A	Y	Y	N	N	N	Y	Y	1
DS22	67	F	N	N/A	Y	more	Y	N	N	N	Y	Y	N	4
DS23	45	M	N	N/A	N	N/A	N	N	N	N	Y	Y	Y	1
DS24	41	F	N	N/A	N	N/A	Y	Y	N	N	N	N	Y	4
DS25	45	M	N	N/A	N	N/A	Y	Y	N	N	N	N	Y	5
DS26	30	M	Y	1	N	N/A	Y	Y	N	N	N	Y	Y	4
DS27	27	M	Y	0	N	N/A	Y	Y	N	N	N	N	Y	5
DS28	24	M	N	N/A	N	N/A	Y	N	N	N	N	Y	Y	5
DS29	36	M	N	N/A	N	N/A	N	N	N	N	N	N	Y	3
DS30	56	M	N	N/A	Y	less	N	N	N	N	Y	Y	Y	1
DS31	48	F	N	N/A	Y	less	N	N	N	N	Y	N	Y	1
DS32	21	M	N	N/A	N	N/A	Y	N	N	N	N	Y	N	3

Participant ID	Age	Sex	Smoke	Yrs Quit	Drugs	Alertness	Caffeine	Alcohol	Head Injury	Act	Meditate	Dexterity	Sports	Athleticism
DS33	28	M	N	N/A	N	N/A	Y	N	N	Y	N	Y	N	3
DS34	25	M	N	N/A	N	N/A	Y	Y	N	N	N	Y	Y	5
DS35	22	F	N	N/A	N	N/A	Y	N	N	Y	N	Y	Y	3
DS36	23	M	N	N/A	N	N/A	Y	Y	N	N	N	Y	Y	4
DS37	23	M	Y	0	Y	less	Y	Y	N	N	N	Y	Y	4
DS38	25	M	N	N/A	Y	less	Y	N	N	N	Y	N	Y	1

Participant ID	Hand	BioTrng	FPS	Adven	Puzzle	Strat	Rhythm	RPG	Sims	SporG	Comp	Paralys	SkinColor	HairCol	HairTextr	Ed
DS01	right	2	3	3	3	3	3	3	2	1	3	0	white	black	straight	18
DS02	left	1	1	1	1	1	1	1	1	1	3	0	darkbrown	black	curly	18
DS03	right	1	1	1	1	1	1	1	1	1	3	0	lightbrown	black	straight	18
DS04	right	1	2	2	2	1	1	1	1	2	2	0	lightbrown	black	curly	14
DS05	right	1	1	1	2	1	1	2	1	1	3	0	lightbrown	black	straight	14
DS06	right	1	1	1	1	1	1	1	1	1	3	0	darkbrown	black	curly	12
DS07	right	1	1	1	1	1	1	1	1	1	3	0	lightbrown	black	straight	14
DS08	right	1	2	2	1	2	1	1	1	2	2	0	lightbrown	black	curly	14
DS09	right	1	1	1	2	1	1	1	1	1	2	0	darkbrown	black	straight	16
DS10	right	1	2	2	2	1	1	1	2	2	3	0	darkbrown	black	curly	16
DS11	left	1	1	1	1	1	1	1	1	1	2	0	lightbrown	gray	curly	16
DS12	right	1	1	1	1	1	1	1	1	1	3	0	lightbrown	black	straight	16
DS13	right	1	2	1	3	1	1	1	2	1	3	0	white	brown	straight	20
DS14	left	2	3	2	2	3	1	2	2	3	3	0	medbrown	black	curly	16
DS15	right	1	1	1	1	1	1	1	1	1	3	0	medbrown	black	curly	20
DS16	right	2	2	1	2	1	2	1	1	1	3	0	medbrown	black	curly	20
DS17	right	2	1	2	2	1	1	1	2	1	3	0	white	brown	straight	18
DS18	right	1	2	2	2	3	1	2	2	3	3	0	white	brown	straight	19
DS19	right	1	2	2	2	2	2	2	1	1	3	0	white	brown	curly	20
DS20	right	1	1	1	3	1	2	1	1	1	3	0	white	brown	straight	20
DS21	right	2	2	2	2	2	2	2	2	2	3	0	white	brown	curly	20
DS22	right	2	1	1	2	1	1	1	1	1	2	2	lightbrown	gray	curly	20
DS23	right	4	1	1	1	1	1	1	1	1	3	19	white	brown	curly	16
DS24	right	1	1	1	2	1	1	1	1	1	3	0	lightbrown	brown	straight	16
DS25	left	1	1	1	1	1	1	1	1	1	3	0	lightbrown	none	none	16

Participant ID	Hand	BioTrng	FPS	Adven	Puzzle	Strat	Rhythm	RPG	Sims	SporG	Comp	Paralys	SkinColor	HairCol	HairTextr	Ed
DS26	right	2	3	3	3	3	2	3	3	2	3	0	white	black	straight	18
DS27	right	2	2	2	2	3	1	2	2	3	3	0	white	brown	straight	18
DS28	right	2	3	2	3	3	2	1	2	2	3	0	lightbrown	black	straight	18
DS29	right	1	3	2	3	3	1	3	2	2	3	0	white	brown	straight	18
DS30	right	1	1	1	2	1	1	1	1	1	3	2	white	brown	straight	16
DS31	right	1	1	1	3	1	1	1	1	1	3	17	white	brown	curly	16
DS32	right	1	3	2	3	3	1	3	1	1	3	0	white	brown	straight	16
DS33	right	3	3	3	3	2	3	3	2	1	3	0	white	brown	straight	18
DS34	right	1	2	1	2	2	1	3	3	3	3	0	white	brown	straight	18
DS35	right	2	2	2	2	1	1	1	1	1	3	0	lightbrown	black	curly	18
DS36	right	1	2	2	2	2	2	2	2	1	3	0	white	brown	straight	16
DS37	right	1	2	2	3	1	3	2	3	1	3	0	lightbrown	black	straight	18
DS38	right	1	3	2	3	3	1	1	3	2	3	3	white	brown	straight	14

Appendix B: Biometric User Profile Questionnaire

Participant ID:	*(For Use by Investigator)*	
Age:		**Sex:** Male Female

Please answer the following questions to the best of your ability. Your identity will be kept private and your answers will be made anonymous if used in any analysis.

Yes **No**

1. Do you smoke or were you a smoker? ☐ ☐

   If you quit smoking, how long ago did you quit? ______________________

2. Are you currently taking any medication, drugs, or vitamins that may affect your alertness?

   (e.g., anti-histamine, anti-depressant, anti-anxiety, recreational drug, Super B complex) ☐ ☐

   If yes, does it make you less alert or more alert than normal for you? *Circle one:* Less More

3. Do you regularly (i.e., daily) drink caffeinated beverages and/or eat chocolate? ☐ ☐
   (e.g., coffee, caffeinated soda, tea, hot chocolate, chocolate bar)

4. Do you regularly drink alcohol (i.e., wine, beer, liquor)? ☐ ☐

5. Have you ever suffered from any short/long-term memory or speech loss due to a concussion or blow to the head? ☐ ☐

6. Do you act or do you consider yourself to be an actor/actress? ☐ ☐

7. Do you regularly (i.e., daily) engage in meditation? ☐ ☐

8. Do you have any dexterity and/or special skills with your hands? ☐ ☐
   (e.g., painting, playing an instrument, other detailed work with your hands)

   If yes, in what area(s)?______________________

9. Do you play any sports or did you play any in the past? ☐ ☐

   If you played sports, what kind did you play and how recently did you play them? (e.g., cross-country runner, 5 years ago; ballroom dance, currently)

   ____

10. Please rate your overall current level of athleticism on a scale from 1-7, where 7 is very athletic such as a trained athlete and 1 is very sedentary. *Circle one:* 1 2 3 4 5 6 7

11. Which hand do you use for writing? *Circle one:* Right Left

12. Have you received any prior training with a direct-brain interface or biometric technology? (e.g., mu-based system, polygraph, fNIR system) *Circle one (hours):* 0 1-3 4-10 11+

    If yes, what type of direct-brain interface or biometric technology and how long ago?
    ____

13. What experience do you have with playing video games?

    Action/First-person shooter games (e.g., Quake)? *Circle one:* None Some Extensive

    Adventure games (e.g., Myst)? *Circle one:* None Some Extensive

    Puzzle games (e.g., Tetris)? *Circle one:* None Some Extensive

    Real-time Strategy games (e.g., StarCraft)? *Circle one:* None Some Extensive

    Rhythm games (e.g., Dance Dance Revolution)? *Circle one:* None Some Extensive

    Role-playing games e.g., Fallout, Final Fantasy)? *Circle one:* None Some Extensive

    Simulation games (e.g., Gran Turismo)? *Circle one:* None Some Extensive

    Sports games (e.g., Madden)? *Circle one:* None Some Extensive

    Other? (Name and Type) __________________ *Circle one:* None Some Extensive

14. How much do you typically use a computer for non-gaming activities?
    Circle one: Hardly Ever A Little Extensively

15. If you suffer from any form of paralysis, how long has it been since the onset of your condition?

    ____

Investigator Notes:

Appendix C: Participant Session Information Sheet

Participant ID	Date	Start time	End time

No.	Question	Response
1.	If you **smoke**, how long ago did you smoke your last cigarette? (hours)	
2.	a. If you drink **caffeinated beverages** or eat **chocolate**, how long ago did you last drink/eat a serving? (hours)	
	b. How much did you consume? (servings, bars)	
3.	a. If you drink **alcohol**, how long ago was your last drink? (hours)	
	b. What type? (i.e., wine, beer, liquor)	
4.	a. Are you currently **hungry**? (yes/no)	
	b. How long ago did you eat your last major meal? (hours)	
5.	Please rate how **rested** you feel on a scale of 1-5, where 5 is the most rested.	
6.	Please rate your current level of **alertness** on a scale of 1-5, where 5 is the most alert.	
7.	Please rate your current level of stress on a scale of 1-5, where 5 is the most stressed.	
8.	Please rate your current level of **anxiety** on a scale of 1-5, where 5 is the most anxious.	

Investigator Notes:

Appendix D: Session Protocol

Orientation

STEP	**TASK**	**INSTRUCTIONS**	**DURATION**	**ELAPSED TIME**
1.	Participant reviews consent form	Please read over the provided consent form (or the form is read aloud) and sign if you agree to participate.	5 min	5 min
2.	Complete initial questionnaires	Please answer questions to the best of your knowledge.	10 min	15 min

System Setup

STEP	**TASK**	**INSTRUCTIONS**	**DURATION**	**ELAPSED TIME**
3.	Operator places sensors for interface *For GSR*: Place electrodes on the index and middle finger of the right hand. *For fNIR:* Place the padded sensor on the left temple (over the language area of the brain) and hold in place using a tennis headband.	*Randomized order of testing* *For GSR:* The electrodes placed on the fingers will send an imperceptible amount of electricity to measure sweat. You should not experience any discomfort so please inform me if you do. *For fNIR:* A sensor producing infrared light placed on the scalp over the language area of the brain will measure oxygenation of the blood. You should not experience any discomfort so please inform me if you do.	2 min	17 min
4.	Conduct manual system calibration	*For GSR:* Stay relaxed or think of a very exciting moment for you. *For fNIR:* Say 'lala' repeatedly in your head or 'count' rapidly in your head.	1 min	18 min
5.	Practice – attain target 5b	Try to move the cursor into the target to the right.	3 x (20 s timeout+10 s breaks) = 1.5 min	19.5 min
6.	Practice – attain target 1b	Same thing but this time, try to move the cursor into the target to the left.	3 x (20 s timeout+10 s breaks) = 1.5 min	21 min
7.	**Break**	We are not recording now. Take a break while remaining in your place. We will begin in a minute.	1 min	22 min

Experiment

STEP	TASK	INSTRUCTIONS	DURATION	ELAPSED TIME
8.	Attain target 4	Try to move the cursor into the target to the right.	6 x (20 s timeout+10 s breaks) = 3 min	25 min
9.	Attain target 1	Try to move the cursor into the target to the left.	6 x (20 s timeout+10 s breaks) = 3 min	28 min
10.	Attain target 3	Try to move the cursor into the target to the right.	6 x (20 s timeout+10 s breaks) = 3 min	31 min
11.	Attain target 2	Try to move the cursor into the target to the left.	6 x (20 s timeout+10 s breaks) = 3 min	34 min
12.	**Break**	We are not recording now. Take a break while remaining in your place. We will begin in a minute.	1 min	35 min
13.	Attain target 2	Try to move the cursor into the target to the left.	6 x (20 s timeout+10 s breaks) = 3 min	38 min
14.	Attain target 4	Try to move the cursor into the target to the right.	6 x (20 s timeout+10 s breaks) = 3 min	41 min
15.	Attain target 3	Try to move the cursor into the target to the right.	6 x (20 s timeout+10 s breaks) = 3 min	44 min
16.	Attain target 1	Try to move the cursor into the target to the left.	6 x (20 s timeout+10 s breaks) = 3 min	47 min
17.	**Break**	We are not recording now. Take a break while remaining in your place. We will begin in a minute.	1 min	48 min
18.	Attain target 1	Try to move the cursor into the target to the left.	6 x (20 s timeout+10 s breaks) = 3 min	51 min
19.	Attain target 3	Try to move the cursor into the target to the right.	6 x (20 s timeout+10 s breaks) = 3 min	54 min
20.	Attain target 4	Try to move the cursor into the target to the right.	6 x (20 s timeout+10 s breaks) = 3 min	57 min
21.	Attain target 2	Try to move the cursor into the target to the left.	6 x (20 s timeout+10 s breaks) = 3 min	60 min
22.	**Break**	We are not recording now. Take a break do what you want to. We will begin again in 5 minutes.	5 min	65 min
23.	**Repeat Steps 3-21 with other Technology**	We will repeat the same protocol using the other technology.	45 min	110 min
24.	Complete exit questionnaire	You have completed the session. Thank you for your time. Please answer questions to the best of your knowledge. Do you have any questions at this time?	5 min	115 min

TOTAL DURATION: Approx. 2 hours (1 hour and 55 min)

Appendix E: BioGauge Protocols for Continuous-Output Transducers

No Control Protocols

NC1: No Control – resting

Description: Record transducer output for 1 minute while participant relaxes in seated position with eyes closed.

Objective: Characterize the transducer's ability to remain neutral when the user is relaxed with eyes closed and there is no intent by the participant to control the transducer

NC2: No Control – passive

Description: Record transducer output for 1 minute while participant relaxes in seated position while simply watching a seascape.

Objective: Indicate the transducer's ability to remain neutral when the user is passively observant, but there is no intent by the participant to make an activation.

NC3: No Control – attentive

Description: Record transducer output for 1 minute while participant relaxes in seated position and performs an active mental search for hidden faces in a picture. The difficulty level is such that the hidden images are not readily apparent but the task is not impossible. The search is non-exhaustive for the participant where they are told to search for images but not told how many images to find.

Objective: Indicate the transducer's ability to remain neutral when the user is attentive, but there is no intent by the participant to make an activation.

Intentional Control Protocols

RC1: Attain Target from Fixed Starting Point

Description: For 1D continuous output transducers, the participant is presented with a 1D space (indicated by a blue bar) and asked to move an indicator to a specific target box. Likewise for 2D continuous output transducers, the participant is presented with a 2D space (indicated by a blue area) and asked to move an indicator to a specific target box. The computer system does not move the indicator at a regular rate, but rather the indicator movement is controlled by the participant. The participant's screen is proportional to the absolute range of transducer values. At the start of a new trial, the indicator is set at a pre-specified starting point along the 1D or 2D space.

Objective: Indicate how quickly and accurately a participant can change from one transducer output level to another

RC2: Attain Target from Fixed Starting Point and Hold for Prescribed Time

Description: For 1D continuous output transducers, the participant is presented with a 1D space (indicated by a blue bar) and asked to move an indicator to a specific target box and hold it within that target box for a predefined time interval. Likewise for 2D continuous output transducers, the participant is presented with a 2D space (indicated by a blue area) and asked to move an indicator to a specific target box and hold it within that target box for a predefined time interval. When the participant moves the indicator within the target box, the box slowly fills in from the edges inward representing a timer for how long the transducer output should be held at a certain level. If feedback is desired, the target box will change color upon entry of the indicator and change back to its original color upon exit of the indicator from the target box. A trial ends after the target box is first reached and exited or upon timeout. After each trial, the target box disappears and is repositioned after a set amount of time. Indicator positioning and movement is the same as above.

Objective: 1) Indicate how quickly and accurately a participant can change from one transducer output level to another; and 2) Indicate how well a participant can maintain a specific output level

Appendix F: Participant Post-Session Questionnaire

Participant ID:	

Please answer the following questions to the best of your ability. Your identity will be kept private and your answers will be made anonymous if used in any analysis.

1. What sort of imagery did you use to control the cursor?
   To move it to the right?

   To move it to the left?

2. How was the experience of the exercise for you? Fun, interesting, boring, tiring, etc.?

3. Were you given enough instructions?

4. What do you think of this research?

5. Would you like to come back?

6. Do you have any additional comments/feedback to the session?

Investigator Notes:

Appendix G: Detailed Descriptive Statistics

Continuous/Scaled Variables

Descriptives

			Statistic	Std. Error
fNIR Success	Mean		.46637	.025726
	95% Confidence Interval for Mean	Lower Bound	.41424	
		Upper Bound	.51849	
	5% Trimmed Mean		.46295	
	Median		.46528	
	Variance		.025	
	Std. Deviation		.158585	
	Minimum		.181	
	Maximum		.833	
	Range		.653	
	Interquartile Range		.23958	
	Skewness		.285	.383
	Kurtosis		-.344	.750
GSR Success	Mean		.35435	.035221
	95% Confidence Interval for Mean	Lower Bound	.28299	
		Upper Bound	.42572	
	5% Trimmed Mean		.34970	
	Median		.35417	
	Variance		.047	
	Std. Deviation		.217120	
	Minimum		.000	
	Maximum		.806	
	Range		.806	
	Interquartile Range		.30382	
	Skewness		-.037	.383
	Kurtosis		-.478	.750
Age	Mean		39.24	2.142
	95% Confidence Interval for Mean	Lower Bound	34.90	
		Upper Bound	43.58	
	5% Trimmed Mean		38.89	
	Median		37.50	
	Variance		174.402	
	Std. Deviation		13.206	
	Minimum		21	
	Maximum		67	
	Range		46	
	Interquartile Range		24.50	
	Skewness		.307	.383
	Kurtosis		-1.204	.750

Descriptives

			Statistic	Std. Error
Athleticism	Mean		3.16	.268
	95% Confidence Interval for Mean	Lower Bound	2.61	
		Upper Bound	3.70	
	5% Trimmed Mean		3.09	
	Median		3.00	
	Variance		2.731	
	Std. Deviation		1.653	
	Minimum		1	
	Maximum		7	
	Range		6	
	Interquartile Range		2.50	
	Skewness		.190	.383
	Kurtosis		-.822	.750
Biometric Training	Mean		1.08	.414
	95% Confidence Interval for Mean	Lower Bound	.24	
		Upper Bound	1.92	
	5% Trimmed Mean		.61	
	Median		.00	
	Variance		6.507	
	Std. Deviation		2.551	
	Minimum		0	
	Maximum		14	
	Range		14	
	Interquartile Range		2.00	
	Skewness		4.022	.383
	Kurtosis		18.621	.750
Yrs with Paralysis	Mean		1.13	.663
	95% Confidence Interval for Mean	Lower Bound	-.21	
		Upper Bound	2.48	
	5% Trimmed Mean		.25	
	Median		.00	
	Variance		16.712	
	Std. Deviation		4.088	
	Minimum		0	
	Maximum		19	
	Range		19	
	Interquartile Range		.00	
	Skewness		4.034	.383
	Kurtosis		15.568	.750

Descriptives

			Statistic	Std. Error
Yrs Education	Mean		17.08	.338
	95% Confidence Interval for Mean	Lower Bound	16.39	
		Upper Bound	17.76	
	5% Trimmed Mean		17.15	
	Median		18.00	
	Variance		4.345	
	Std. Deviation		2.084	
	Minimum		12	
	Maximum		20	
	Range		8	
	Interquartile Range		2.00	
	Skewness		-.318	.383
	Kurtosis		-.459	.750

Categorical Variables

Sex

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	13	34.2	34.2	34.2
	Male	25	65.8	65.8	100.0
	Total	38	100.0	100.0	

Smoker

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	28	73.7	73.7	73.7
	Yes	10	26.3	26.3	100.0
	Total	38	100.0	100.0	

Drugs

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	31	81.6	81.6	81.6
	Yes	7	18.4	18.4	100.0
	Total	38	100.0	100.0	

Regular Caffeine

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	11	28.9	28.9	28.9
	Yes	27	71.1	71.1	100.0
	Total	38	100.0	100.0	

Regular Alcohol

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	26	68.4	68.4	68.4
	Yes	12	31.6	31.6	100.0
	Total	38	100.0	100.0	

Head Injury

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	37	97.4	97.4	97.4
	Yes	1	2.6	2.6	100.0
	Total	38	100.0	100.0	

Acting Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	35	92.1	92.1	92.1
	Yes	3	7.9	7.9	100.0
	Total	38	100.0	100.0	

Meditation Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	31	81.6	81.6	81.6
	Yes	7	18.4	18.4	100.0
	Total	38	100.0	100.0	

Dexterity

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	15	39.5	39.5	39.5
	Yes	23	60.5	60.5	100.0
	Total	38	100.0	100.0	

Play Sports

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	7	18.4	18.4	18.4
	Yes	31	81.6	81.6	100.0
	Total	38	100.0	100.0	

Handedness

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Left	4	10.5	10.5	10.5
	Right	34	89.5	89.5	100.0
	Total	38	100.0	100.0	

First-Person Shooter Games

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	17	44.7	44.7	44.7
	Some	13	34.2	34.2	78.9
	Extensive	8	21.1	21.1	100.0
	Total	38	100.0	100.0	

Adventure Games

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	19	50.0	50.0	50.0
	Some	16	42.1	42.1	92.1
	Extensive	3	7.9	7.9	100.0
	Total	38	100.0	100.0	

Puzzle Games

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	10	26.3	26.3	26.3
	Some	17	44.7	44.7	71.1
	Extensive	11	28.9	28.9	100.0
	Total	38	100.0	100.0	

Strategy Games

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	23	60.5	60.5	60.5
	Some	6	15.8	15.8	76.3
	Extensive	9	23.7	23.7	100.0
	Total	38	100.0	100.0	

Rhythm Games

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	28	73.7	73.7	73.7
	Some	7	18.4	18.4	92.1
	Extensive	3	7.9	7.9	100.0
	Total	38	100.0	100.0	

Role-Playing Games

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	24	63.2	63.2	63.2
	Some	8	21.1	21.1	84.2
	Extensive	6	15.8	15.8	100.0
	Total	38	100.0	100.0	

Simulations

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	22	57.9	57.9	57.9
	Some	12	31.6	31.6	89.5
	Extensive	4	10.5	10.5	100.0
	Total	38	100.0	100.0	

SportGames

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	26	68.4	68.4	68.4
	Some	8	21.1	21.1	89.5
	Extensive	4	10.5	10.5	100.0
	Total	38	100.0	100.0	

ComputerUse

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Hardly Ever	1	2.6	2.6	2.6
	A Little	5	13.2	13.2	15.8
	Extensively	32	84.2	84.2	100.0
	Total	38	100.0	100.0	

Skin Color

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	White	18	47.4	47.4	47.4
	LightBrown	13	34.2	34.2	81.6
	MediumBrown	3	7.9	7.9	89.5
	DarkBrown	4	10.5	10.5	100.0
	Total	38	100.0	100.0	

Hair Color

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Blond/None	1	2.6	2.6	2.6
	Brown	17	44.7	44.7	47.4
	Black	18	47.4	47.4	94.7
	Gray	2	5.3	5.3	100.0
	Total	38	100.0	100.0	

Hair Texture

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	1	2.6	2.6	2.6
	Straight	22	57.9	57.9	60.5
	Curly	15	39.5	39.5	100.0
	Total	38	100.0	100.0	

Appendix H: Detailed Performance Results with fNIR

Yellow shading indicates averaged results for able-bodied participants and green shading indicates averaged results for participants with ALS (DS22, 23, 30, 31, and 38). Bold values are the overall measures of success taken as an average across the entire set.

Participant ID	Order Ran	Run No.	p06	p07	p08	p09	Average Success
			far right	far left	mid right	mid left	
DS01	1	1	0.500	0.000	0.000	0.000	0.125
		2	0.500	0.500	0.500	0.000	0.375
		3	0.833	0.500	0.833	0.667	0.708
		Success	0.611	0.333	0.444	0.222	**0.403**
DS02	1	1	0.833	0.000	0.333	0.500	0.417
		2	0.333	0.167	0.167	0.000	0.167
		3	0.333	0.833	0.000	0.000	0.292
		Success	0.500	0.333	0.167	0.167	**0.292**
DS03	2	1	0.833	0.000	1.000	0.667	0.625
		2	0.000	0.000	0.500	0.000	0.125
		3	0.333	0.500	0.000	0.000	0.208
		Success	0.389	0.167	0.500	0.222	**0.319**
DS04	1	1	0.000	0.667	0.000	0.667	0.333
		2	0.500	0.333	0.167	0.000	0.250
		3	0.833	0.500	0.833	0.667	0.708
		Success	0.444	0.500	0.333	0.444	**0.431**
DS05	2	1	0.667	1.000	0.000	0.500	0.542
		2	0.167	0.000	0.833	0.333	0.333
		3	0.167	0.000	0.167	1.000	0.333
		Success	0.333	0.333	0.333	0.611	**0.403**
DS06	1	1	0.333	0.667	0.833	0.333	0.542
		2	0.500	0.333	0.833	0.500	0.542
		3	0.500	0.000	0.667	0.167	0.333
		Success	0.444	0.333	0.778	0.333	**0.472**
DS07	1	1	0.333	0.000	0.333	0.000	0.167
		2	0.000	0.000	0.333	0.000	0.083
		3	0.500	1.000	1.000	0.167	0.667
		Success	0.278	0.333	0.556	0.056	**0.306**

Participant ID	Order Ran	Run No.	p06	p07	p08	p09	Average Success
DS08	2	1	0.000	1.000	0.333	0.333	0.417
		2	1.000	0.000	0.167	0.000	0.292
		3	0.000	0.333	0.167	0.000	0.125
		Success	0.333	0.444	0.222	0.111	**0.278**
DS09	1	1	0.000	0.833	0.000	0.833	0.417
		2	1.000	0.833	0.833	0.000	0.667
		3	0.667	0.667	0.333	0.833	0.625
		Success	0.556	0.778	0.389	0.556	**0.569**
DS10	2	1	0.500	0.333	0.667	0.833	0.583
		2	0.500	1.000	1.000	0.500	0.750
		3	0.667	0.333	0.833	0.667	0.625
		Success	0.556	0.556	0.833	0.667	**0.653**
DS11	2	1	0.333	0.167	0.167	0.667	0.333
		2	0.000	0.833	0.000	1.000	0.458
		3	0.500	0.000	0.667	0.833	0.500
		Success	0.278	0.333	0.278	0.833	**0.431**
DS12	1	1	0.333	0.000	0.000	0.000	0.083
		2	0.333	0.167	0.333	0.000	0.208
		3	0.500	0.000	0.500	0.500	0.375
		Success	0.389	0.056	0.278	0.167	**0.222**
DS13	1	1	0.333	0.000	0.833	0.000	0.292
		2	0.833	0.500	0.667	0.500	0.625
		3	0.833	0.667	0.500	0.500	0.625
		Success	0.667	0.389	0.667	0.333	**0.514**
DS14	2	1	0.833	0.000	1.000	0.000	0.458
		2	0.333	1.000	0.833	1.000	0.792
		3	0.000	1.000	0.000	0.333	0.333
		Success	0.389	0.667	0.611	0.444	**0.528**
DS15	1	1	0.500	0.000	0.000	0.667	0.292
		2	0.500	0.000	0.500	1.000	0.500
		3	1.000	0.833	0.667	1.000	0.875
		Success	0.667	0.278	0.389	0.889	**0.556**
DS16	2	1	0.833	0.000	0.500	1.000	0.583
		2	0.833	0.833	0.333	1.000	0.750
		3	1.000	0.333	0.500	0.500	0.583
		Success	0.889	0.389	0.444	0.833	**0.639**

Participant ID	Order Ran	Run No.	p06	p07	p08	p09	Average Success
DS17	2	1	1.000	0.000	0.333	0.000	0.333
		2	0.667	0.667	0.833	0.333	0.625
		3	0.500	0.000	0.500	0.000	0.250
		Success	0.722	0.222	0.556	0.111	**0.403**
DS18	1	1	0.833	0.667	0.833	0.500	0.708
		2	0.833	0.500	0.833	1.000	0.792
		3	0.667	0.500	1.000	1.000	0.792
		Success	0.778	0.556	0.889	0.833	**0.764**
DS19	2	1	0.833	0.167	0.500	1.000	0.625
		2	1.000	1.000	0.833	1.000	0.958
		3	1.000	0.833	0.833	1.000	0.917
		Success	0.944	0.667	0.722	1.000	**0.833**
DS20	1	1	0.500	0.833	0.667	0.000	0.500
		2	0.500	0.667	0.000	0.667	0.458
		3	0.500	0.667	0.500	0.833	0.625
		Success	0.500	0.722	0.389	0.500	**0.528**
DS21	2	1	0.500	0.500	0.167	1.000	0.542
		2	0.667	0.000	0.667	0.167	0.375
		3	0.500	0.000	0.833	0.833	0.542
		Success	0.556	0.167	0.556	0.667	**0.486**
DS22	1	1	0.167	0.000	0.833	0.833	0.458
		2	0.000	0.167	0.000	0.000	0.042
		3	0.833	0.000	0.833	0.167	0.458
		Success	0.333	0.056	0.556	0.333	**0.319**
DS23	2	1	1.000	0.667	0.667	0.333	0.667
		2	0.500	0.167	0.833	1.000	0.625
		3	0.833	0.333	0.833	0.333	0.583
		Success	0.778	0.389	0.778	0.556	**0.625**
DS24	2	1	0.000	0.000	0.167	0.833	0.250
		2	0.500	0.000	0.167	0.500	0.292
		3	0.000	0.000	0.000	0.000	0.000
		Success	0.167	0.000	0.111	0.444	**0.181**
DS25	1	1	0.667	0.500	0.000	0.000	0.292
		2	0.167	0.333	0.167	0.000	0.167
		3	0.167	0.333	0.167	0.000	0.167
		Success	0.333	0.389	0.111	0.000	**0.208**

Participant ID	Order Ran	Run No.	p06	p07	p08	p09	Average Success
DS26	1	1	0.000	0.000	0.833	0.000	0.208
		2	0.667	0.667	0.500	0.833	0.667
		3	0.833	0.167	0.833	0.000	0.458
		Success	0.500	0.278	0.722	0.278	**0.444**
DS27	2	1	0.667	0.667	0.500	0.167	0.500
		2	0.833	0.500	0.500	0.167	0.500
		3	1.000	0.667	1.000	1.000	0.917
		Success	0.833	0.611	0.667	0.444	**0.639**
DS28	2	1	0.333	0.000	0.500	0.833	0.417
		2	0.500	0.167	0.000	0.000	0.167
		3	0.333	0.500	0.000	0.167	0.250
		Success	0.389	0.222	0.167	0.333	**0.278**
DS29	1	1	0.167	0.667	1.000	0.167	0.500
		2	0.333	0.667	0.000	0.500	0.375
		3	0.500	0.833	0.500	0.500	0.583
		Success	0.333	0.722	0.500	0.389	**0.486**
DS30	2	1	0.667	0.000	0.833	0.667	0.542
		2	0.833	0.000	0.833	1.000	0.667
		3	0.500	0.000	0.500	0.000	0.250
		Success	0.667	0.000	0.722	0.556	**0.486**
DS31	1	1	0.167	0.167	1.000	0.333	0.417
		2	0.833	0.000	0.000	0.000	0.208
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.500	0.083	0.500	0.167	**0.313**
DS32	2	1	0.833	0.167	0.333	0.333	0.417
		2	0.500	0.833	1.000	0.333	0.667
		3	0.167	0.167	0.667	1.000	0.500
		Success	0.500	0.389	0.667	0.556	**0.528**
DS33	1	1	0.667	0.000	0.667	0.667	0.500
		2	0.167	0.333	0.333	0.833	0.417
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.417	0.167	0.500	0.750	**0.458**
DS34	2	1	0.500	0.667	0.833	0.500	0.625
		2	0.333	0.500	1.000	0.333	0.542
		3	0.667	0.000	0.500	0.000	0.292
		Success	0.500	0.389	0.778	0.278	**0.486**

Participant ID	Order Ran	Run No.	p06	p07	p08	p09	Average Success
DS35	2	1	0.833	0.333	0.833	0.500	0.625
		2	0.667	0.667	1.000	1.000	0.833
		3	1.000	0.667	1.000	0.167	0.708
		Success	0.833	0.556	0.944	0.556	**0.722**
DS36	1	1	0.000	0.500	0.500	0.167	0.292
		2	0.500	0.500	0.167	0.500	0.417
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.250	0.500	0.333	0.333	**0.354**
DS37	2	1	0.667	0.833	1.000	1.000	0.875
		2	0.167	0.000	1.000	0.667	0.458
		3	0.833	0.667	0.833	0.833	0.792
		Success	0.556	0.500	0.944	0.833	**0.708**
DS38	1	1	0.500	0.500	0.833	0.000	0.458
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.500	0.500	0.833	0.000	**0.458**

Appendix I: Detailed Performance Results with GSR

Yellow shading indicates averaged results for able-bodied participants and green shading indicates averaged results for participants with ALS (DS22, 23, 30, 31, and 38). Bold values are the overall measures of success taken as an average across the entire set.

Participant	Order	Run	p10	p11	p12	p13	Average Success
			far right	far left	mid right	mid left	
DS01	2	1	0.167	0.000	0.333	0.333	0.208
		2	0.333	0.667	0.000	0.000	0.250
		3	1.000	0.167	0.667	0.167	0.500
		Success	0.500	0.278	0.333	0.167	**0.319**
DS02	2	1	0.000	0.000	0.000	0.000	0.000
		2	0.000	0.833	0.000	0.000	0.208
		3	0.000	0.333	0.000	0.833	0.292
		Success	0.000	0.389	0.000	0.278	**0.167**
DS03	1	1	0.500	1.000	0.500	0.500	0.625
		2	0.000	0.000	0.000	0.833	0.208
		3	0.500	0.500	0.000	0.000	0.250
		Success	0.333	0.500	0.167	0.444	**0.361**
DS04	2	1	0.000	0.667	0.833	0.000	0.375
		2	0.000	0.167	0.500	0.833	0.375
		3	0.500	0.167	0.500	0.000	0.292
		Success	0.167	0.333	0.611	0.278	**0.347**
DS05	1	1	0.833	0.167	1.000	0.667	0.667
		2	0.000	0.833	0.000	0.667	0.375
		3	0.000	0.333	0.167	0.333	0.208
		Success	0.278	0.444	0.389	0.556	**0.417**
DS06	2	1	0.500	0.000	0.500	0.500	0.375
		2	1.000	0.500	0.833	0.167	0.625
		3	0.500	0.000	0.833	0.000	0.333
		Success	0.667	0.167	0.722	0.222	**0.444**
DS07	2	1	0.333	0.000	0.167	0.000	0.125
		2	0.667	0.500	1.000	1.000	0.792
		3	0.500	0.833	0.000	0.500	0.458
		Success	0.500	0.444	0.389	0.500	**0.458**

Participant	Order	Run	p10	p11	p12	p13	Average Success
DS08	1	1	0.333	0.500	0.833	0.000	0.417
		2	0.000	0.000	0.000	0.167	0.042
		3	0.500	0.167	0.500	0.000	0.292
		Success	0.278	0.222	0.444	0.056	**0.250**
DS09	2	1	0.000	0.000	0.000	0.000	0.000
		2	0.000	0.000	0.000	0.000	0.000
		3	0.000	0.333	0.000	0.000	0.083
		Success	0.000	0.111	0.000	0.000	**0.028**
DS10	1	1	0.333	0.333	0.167	0.333	0.292
		2	0.000	0.000	0.000	0.667	0.167
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.167	0.167	0.083	0.500	**0.229**
DS11	1	1	0.833	0.000	0.000	N/A	0.278
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.833	0.000	0.000	N/A	**0.278**
DS12	2	1	0.333	0.333	1.000	0.333	0.500
		2	0.167	0.000	0.167	0.000	0.083
		3	0.000	0.667	0.333	0.000	0.250
		Success	0.167	0.333	0.500	0.111	**0.278**
DS13	2	1	0.167	0.833	0.500	0.500	0.500
		2	0.833	0.167	0.833	0.500	0.583
		3	0.667	0.833	0.000	0.167	0.417
		Success	0.556	0.611	0.444	0.389	**0.500**
DS14	1	1	0.000	0.833	0.167	0.167	0.292
		2	0.000	0.167	0.000	0.500	0.167
		3	0.000	0.333	0.000	0.000	0.083
		Success	0.000	0.444	0.056	0.222	**0.181**
DS15	2	1	0.167	0.000	0.000	0.667	0.208
		2	0.000	N/A	0.000	0.667	0.222
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.083	0.000	0.000	0.667	**0.188**
DS16	1	1	0.000	0.000	N/A	N/A	0.000
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.000	0.000	N/A	N/A	**0.000**

Participant	Order	Run	p10	p11	p12	p13	Average Success
DS17	1	1	N/A	N/A	N/A	N/A	N/A
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	N/A	N/A	N/A	N/A	**0.000**
DS18	2	1	0.833	0.000	1.000	1.000	0.708
		2	0.833	0.167	0.833	0.167	0.500
		3	0.667	1.000	0.667	1.000	0.833
		Success	0.778	0.389	0.833	0.722	**0.681**
DS19	1	1	0.667	0.000	0.333	0.667	0.417
		2	0.833	0.500	0.667	0.167	0.542
		3	0.167	1.000	1.000	1.000	0.792
		Success	0.556	0.500	0.667	0.611	**0.583**
DS20	2	1	0.833	0.333	0.000	0.500	0.417
		2	0.667	0.667	0.000	0.667	0.500
		3	0.667	1.000	0.000	0.500	0.542
		Success	0.722	0.667	0.000	0.556	**0.486**
DS21	1	1	0.667	0.333	0.333	0.500	0.458
		2	0.333	0.500	0.500	0.000	0.333
		3	0.167	0.333	0.333	0.500	0.333
		Success	0.389	0.389	0.389	0.333	**0.375**
DS22	2	1	N/A	N/A	N/A	N/A	N/A
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	N/A	N/A	N/A	N/A	**0.000**
DS23	1	1	0.667	0.000	0.500	0.333	0.375
		2	0.000	0.667	0.833	0.333	0.458
		3	0.000	0.833	0.833	0.500	0.542
		Success	0.222	0.500	0.722	0.389	**0.458**
DS24	1	1	0.500	0.000	0.667	0.000	0.292
		2	0.500	0.500	0.167	0.833	0.500
		3	0.333	0.667	0.000	0.000	0.250
		Success	0.444	0.389	0.278	0.278	**0.347**
DS25	2	1	1.000	0.667	0.000	0.667	0.583
		2	0.167	0.333	0.333	0.500	0.333
		3	0.500	0.000	1.000	0.167	0.417
		Success	0.556	0.333	0.444	0.444	**0.444**

Participant	Order	Run	p10	p11	p12	p13	Average Success
DS26	2	1	0.167	0.667	0.333	0.333	0.375
		2	0.167	0.167	0.167	0.333	0.208
		3	0.833	0.833	0.000	0.167	0.458
		Success	0.389	0.556	0.167	0.278	**0.347**
DS27	1	1	0.833	0.667	1.000	0.667	0.792
		2	0.167	0.167	0.500	0.167	0.250
		3	0.000	0.333	0.667	0.500	0.375
		Success	0.333	0.389	0.722	0.444	**0.472**
DS28	1	1	0.500	0.333	0.167	0.333	0.333
		2	0.167	0.833	0.500	0.833	0.583
		3	0.167	0.833	0.667	0.167	0.458
		Success	0.278	0.667	0.444	0.444	**0.458**
DS29	2	1	0.333	0.500	0.167	0.667	0.417
		2	0.333	0.667	0.500	1.000	0.625
		3	0.500	0.167	1.000	0.833	0.625
		Success	0.389	0.444	0.556	0.833	**0.556**
DS30	1	1	N/A	N/A	N/A	N/A	N/A
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	N/A	N/A	N/A	N/A	**0.000**
DS31	2	1	N/A	N/A	N/A	N/A	N/A
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	N/A	N/A	N/A	N/A	**0.000**
DS32	1	1	0.833	1.000	0.833	1.000	0.917
		2	1.000	0.500	0.500	0.667	0.667
		3	1.000	0.833	0.833	0.333	0.750
		Success	0.944	0.778	0.722	0.667	**0.778**
DS33	2	1	0.000	0.167	0.000	0.500	0.167
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.000	0.167	0.000	0.500	**0.167**
DS34	1	1	0.833	0.833	1.000	0.667	0.833
		2	1.000	1.000	0.667	0.667	0.833
		3	0.667	0.667	1.000	0.667	0.750
		Success	0.833	0.833	0.889	0.667	**0.806**

Participant	Order	Run	p10	p11	p12	p13	Average Success
DS35	1	1	0.333	0.500	0.000	0.000	0.208
		2	0.667	0.667	0.333	0.833	0.625
		3	0.167	0.000	0.500	0.000	0.167
		Success	0.389	0.389	0.278	0.278	**0.333**
DS36	2	1	0.333	0.000	0.667	1.000	0.500
		2	0.833	1.000	0.833	0.500	0.792
		3	0.333	0.833	0.333	0.333	0.458
		Success	0.500	0.611	0.611	0.611	**0.583**
DS37	1	1	0.667	0.833	0.833	0.167	0.625
		2	0.833	0.000	0.500	0.333	0.417
		3	1.000	0.500	1.000	0.833	0.833
		Success	0.833	0.444	0.778	0.444	**0.625**
DS38	2	1	0.750	0.333	0.667	0.333	0.521
		2	N/A	N/A	N/A	N/A	N/A
		3	N/A	N/A	N/A	N/A	N/A
		Success	0.750	0.333	0.667	0.333	**0.521**

Appendix J: Explored Population Differences

Descriptive Statistics

ALS Patient		N	Minimum	Maximum	Mean	Std. Deviation
No	fNIR Success	33	.181	.833	.47033	.163851
	GSR Success	33	.000	.806	.37837	.202323
	Age	33	21	59	37.88	12.534
	Athleticism	33	1	7	3.39	1.580
	Yrs with Paralysis	33	0	0	.00	.000
	Yrs Education	33	12	20	17.18	2.083
	Valid N (listwise)	33				
Yes	fNIR Success	5	.313	.625	.44021	.129870
	GSR Success	5	.000	.521	.19587	.269115
	Age	5	25	67	48.20	15.515
	Athleticism	5	1	4	1.60	1.342
	Yrs with Paralysis	5	2	19	8.60	8.620
	Yrs Education	5	14	20	16.40	2.191
	Valid N (listwise)	5				

Ran First

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	GSR Ran First	18	54.5	54.5	54.5
		fNIR Ran First	15	45.5	45.5	100.0
		Total	33	100.0	100.0	
Yes	Valid	GSR Ran First	1	20.0	20.0	20.0
		fNIR Ran First	4	80.0	80.0	100.0
		Total	5	100.0	100.0	

Sex

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	Female	11	33.3	33.3	33.3
		Male	22	66.7	66.7	100.0
		Total	33	100.0	100.0	
Yes	Valid	Female	2	40.0	40.0	40.0
		Male	3	60.0	60.0	100.0
		Total	5	100.0	100.0	

Smoker

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	23	69.7	69.7	69.7
		Yes	10	30.3	30.3	100.0
		Total	33	100.0	100.0	
Yes	Valid	No	5	100.0	100.0	100.0

Drugs

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	30	90.9	90.9	90.9
		Yes	3	9.1	9.1	100.0
		Total	33	100.0	100.0	
Yes	Valid	No	1	20.0	20.0	20.0
		Yes	4	80.0	80.0	100.0
		Total	5	100.0	100.0	

Regular Caffeine

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	8	24.2	24.2	24.2
		Yes	25	75.8	75.8	100.0
		Total	33	100.0	100.0	
Yes	Valid	No	3	60.0	60.0	60.0
		Yes	2	40.0	40.0	100.0
		Total	5	100.0	100.0	

Regular Alcohol

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	21	63.6	63.6	63.6
		Yes	12	36.4	36.4	100.0
		Total	33	100.0	100.0	
Yes	Valid	No	5	100.0	100.0	100.0

Head Injury

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	32	97.0	97.0	97.0
		Yes	1	3.0	3.0	100.0
		Total	33	100.0	100.0	
Yes	Valid	No	5	100.0	100.0	100.0

Acting Experience

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	30	90.9	90.9	90.9
		Yes	3	9.1	9.1	100.0
		Total	33	100.0	100.0	
Yes	Valid	No	5	100.0	100.0	100.0

Meditation Experience

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	31	93.9	93.9	93.9
		Yes	2	6.1	6.1	100.0
		Total	33	100.0	100.0	
Yes	Valid	Yes	5	100.0	100.0	100.0

Dexterity

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	13	39.4	39.4	39.4
		Yes	20	60.6	60.6	100.0
		Total	33	100.0	100.0	
Yes	Valid	No	2	40.0	40.0	40.0
		Yes	3	60.0	60.0	100.0
		Total	5	100.0	100.0	

Play Sports

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	No	6	18.2	18.2	18.2
		Yes	27	81.8	81.8	100.0
		Total	33	100.0	100.0	
Yes	Valid	No	1	20.0	20.0	20.0
		Yes	4	80.0	80.0	100.0
		Total	5	100.0	100.0	

Biometric Training

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	0	23	69.7	69.7	69.7
		2	9	27.3	27.3	97.0
		7	1	3.0	3.0	100.0
		Total	33	100.0	100.0	
Yes	Valid	0	3	60.0	60.0	60.0
		2	1	20.0	20.0	80.0
		14	1	20.0	20.0	100.0
		Total	5	100.0	100.0	

First-Person Shooter Games

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	13	39.4	39.4	39.4
		Some	13	39.4	39.4	78.8
		Extensive	7	21.2	21.2	100.0
		Total	33	100.0	100.0	
Yes	Valid	None	4	80.0	80.0	80.0
		Extensive	1	20.0	20.0	100.0
		Total	5	100.0	100.0	

Adventure Games

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	15	45.5	45.5	45.5
		Some	15	45.5	45.5	90.9
		Extensive	3	9.1	9.1	100.0
		Total	33	100.0	100.0	
Yes	Valid	None	4	80.0	80.0	80.0
		Some	1	20.0	20.0	100.0
		Total	5	100.0	100.0	

Puzzle Games

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	9	27.3	27.3	27.3
		Some	15	45.5	45.5	72.7
		Extensive	9	27.3	27.3	100.0
		Total	33	100.0	100.0	
Yes	Valid	None	1	20.0	20.0	20.0
		Some	2	40.0	40.0	60.0
		Extensive	2	40.0	40.0	100.0
		Total	5	100.0	100.0	

Strategy Games

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	19	57.6	57.6	57.6
		Some	6	18.2	18.2	75.8
		Extensive	8	24.2	24.2	100.0
		Total	33	100.0	100.0	
Yes	Valid	None	4	80.0	80.0	80.0
		Extensive	1	20.0	20.0	100.0
		Total	5	100.0	100.0	

Rhythm Games

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	23	69.7	69.7	69.7
		Some	7	21.2	21.2	90.9
		Extensive	3	9.1	9.1	100.0
		Total	33	100.0	100.0	
Yes	Valid	None	5	100.0	100.0	100.0

Role-Playing Games

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	19	57.6	57.6	57.6
		Some	8	24.2	24.2	81.8
		Extensive	6	18.2	18.2	100.0
		Total	33	100.0	100.0	
Yes	Valid	None	5	100.0	100.0	100.0

Simulations

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	18	54.5	54.5	54.5
		Some	12	36.4	36.4	90.9
		Extensive	3	9.1	9.1	100.0
		Total	33	100.0	100.0	
Yes	Valid	None	4	80.0	80.0	80.0
		Extensive	1	20.0	20.0	100.0
		Total	5	100.0	100.0	

SportGames

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	22	66.7	66.7	66.7
		Some	7	21.2	21.2	87.9
		Extensive	4	12.1	12.1	100.0
		Total	33	100.0	100.0	
Yes	Valid	None	4	80.0	80.0	80.0
		Some	1	20.0	20.0	100.0
		Total	5	100.0	100.0	

ComputerUse

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	A Little	4	12.1	12.1	12.1
		Extensively	29	87.9	87.9	100.0
		Total	33	100.0	100.0	
Yes	Valid	Hardly Ever	1	20.0	20.0	20.0
		A Little	1	20.0	20.0	40.0
		Extensively	3	60.0	60.0	100.0
		Total	5	100.0	100.0	

Skin Color

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	White	14	42.4	42.4	42.4
		LightBrown	12	36.4	36.4	78.8
		MediumBrown	3	9.1	9.1	87.9
		DarkBrown	4	12.1	12.1	100.0
		Total	33	100.0	100.0	
Yes	Valid	White	4	80.0	80.0	80.0
		LightBrown	1	20.0	20.0	100.0
		Total	5	100.0	100.0	

Hair Color

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	Blond/None	1	3.0	3.0	3.0
		Brown	13	39.4	39.4	42.4
		Black	18	54.5	54.5	97.0
		Gray	1	3.0	3.0	100.0
		Total	33	100.0	100.0	
Yes	Valid	Brown	4	80.0	80.0	80.0
		Gray	1	20.0	20.0	100.0
		Total	5	100.0	100.0	

Hair Texture

ALS Patient			Frequency	Percent	Valid Percent	Cumulative Percent
No	Valid	None	1	3.0	3.0	3.0
		Straight	20	60.6	60.6	63.6
		Curly	12	36.4	36.4	100.0
		Total	33	100.0	100.0	
Yes	Valid	Straight	2	40.0	40.0	40.0
		Curly	3	60.0	60.0	100.0
		Total	5	100.0	100.0	

Mann-Whitney U Test

Test Statistics[b]

	fNIR Success	GSR Success	Age	Athleticism	Biometric Training	Yrs with Paralysis	Yrs Education
Mann-Whitney U	74.000	51.000	49.500	30.500	70.000	.000	61.500
Wilcoxon W	89.000	66.000	610.500	45.500	631.000	561.000	76.500
Z	-.368	-1.363	-1.427	-2.288	-.663	-6.064	-.941
Asymp. Sig. (2-tailed)	.713	.173	.154	.022	.507	.000	.347
Exact Sig. [2*(1-tailed Sig.)]	.738[a]	.187[a]	.159[a]	.021[a]	.615[a]	.000[a]	.376[a]

a. Not corrected for ties.

b. Grouping Variable: ALS Patient

Chi-Square Tests

ALS Patient * Ran First

Crosstab

			Ran First		
			GSR Ran First	fNIR Ran First	Total
ALS Patient	No	Count	18	15	33
		Expected Count	16.5	16.5	33.0
		% within ALS Patient	54.5%	45.5%	100.0%
		% within Ran First	94.7%	78.9%	86.8%
		% of Total	47.4%	39.5%	86.8%
	Yes	Count	1	4	5
		Expected Count	2.5	2.5	5.0
		% within ALS Patient	20.0%	80.0%	100.0%
		% within Ran First	5.3%	21.1%	13.2%
		% of Total	2.6%	10.5%	13.2%
Total		Count	19	19	38
		Expected Count	19.0	19.0	38.0
		% within ALS Patient	50.0%	50.0%	100.0%
		% within Ran First	100.0%	100.0%	100.0%
		% of Total	50.0%	50.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.073[b]	1	.150		
Continuity Correction[a]	.921	1	.337		
Likelihood Ratio	2.201	1	.138		
Fisher's Exact Test				.340	.170
Linear-by-Linear Association	2.018	1	.155		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 2.50.

ALS Patient * Sex

Crosstab

			Sex		Total
			Female	Male	
ALS Patient	No	Count	11	22	33
		Expected Count	11.3	21.7	33.0
		% within ALS Patient	33.3%	66.7%	100.0%
		% within Sex	84.6%	88.0%	86.8%
		% of Total	28.9%	57.9%	86.8%
	Yes	Count	2	3	5
		Expected Count	1.7	3.3	5.0
		% within ALS Patient	40.0%	60.0%	100.0%
		% within Sex	15.4%	12.0%	13.2%
		% of Total	5.3%	7.9%	13.2%
Total		Count	13	25	38
		Expected Count	13.0	25.0	38.0
		% within ALS Patient	34.2%	65.8%	100.0%
		% within Sex	100.0%	100.0%	100.0%
		% of Total	34.2%	65.8%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.086[b]	1	.770		
Continuity Correction[a]	.000	1	1.000		
Likelihood Ratio	.084	1	.772		
Fisher's Exact Test				1.000	.567
Linear-by-Linear Association	.083	1	.773		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.71.

ALS Patient * Smoker

Crosstab

			Smoker		
			No	Yes	Total
ALS Patient	No	Count	23	10	33
		Expected Count	24.3	8.7	33.0
		% within ALS Patient	69.7%	30.3%	100.0%
		% within Smoker	82.1%	100.0%	86.8%
		% of Total	60.5%	26.3%	86.8%
	Yes	Count	5	0	5
		Expected Count	3.7	1.3	5.0
		% within ALS Patient	100.0%	.0%	100.0%
		% within Smoker	17.9%	.0%	13.2%
		% of Total	13.2%	.0%	13.2%
Total		Count	28	10	38
		Expected Count	28.0	10.0	38.0
		% within ALS Patient	73.7%	26.3%	100.0%
		% within Smoker	100.0%	100.0%	100.0%
		% of Total	73.7%	26.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.056[b]	1	.152		
Continuity Correction[a]	.790	1	.374		
Likelihood Ratio	3.316	1	.069		
Fisher's Exact Test				.298	.196
Linear-by-Linear Association	2.002	1	.157		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.32.

ALS Patient * Drugs

Crosstab

			Drugs		
			No	Yes	Total
ALS Patient	No	Count	30	3	33
		Expected Count	26.9	6.1	33.0
		% within ALS Patient	90.9%	9.1%	100.0%
		% within Drugs	96.8%	42.9%	86.8%
		% of Total	78.9%	7.9%	86.8%
	Yes	Count	1	4	5
		Expected Count	4.1	.9	5.0
		% within ALS Patient	20.0%	80.0%	100.0%
		% within Drugs	3.2%	57.1%	13.2%
		% of Total	2.6%	10.5%	13.2%
Total		Count	31	7	38
		Expected Count	31.0	7.0	38.0
		% within ALS Patient	81.6%	18.4%	100.0%
		% within Drugs	100.0%	100.0%	100.0%
		% of Total	81.6%	18.4%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	14.528[b]	1	.000		
Continuity Correction[a]	10.193	1	.001		
Likelihood Ratio	11.197	1	.001		
Fisher's Exact Test				.002	.002
Linear-by-Linear Association	14.146	1	.000		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is .92.

ALS Patient * Regular Caffeine

Crosstab

			Regular Caffeine		Total
			No	Yes	
ALS Patient	No	Count	8	25	33
		Expected Count	9.6	23.4	33.0
		% within ALS Patient	24.2%	75.8%	100.0%
		% within Regular Caffeine	72.7%	92.6%	86.8%
		% of Total	21.1%	65.8%	86.8%
	Yes	Count	3	2	5
		Expected Count	1.4	3.6	5.0
		% within ALS Patient	60.0%	40.0%	100.0%
		% within Regular Caffeine	27.3%	7.4%	13.2%
		% of Total	7.9%	5.3%	13.2%
Total		Count	11	27	38
		Expected Count	11.0	27.0	38.0
		% within ALS Patient	28.9%	71.1%	100.0%
		% within Regular Caffeine	100.0%	100.0%	100.0%
		% of Total	28.9%	71.1%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.699[b]	1	.100		
Continuity Correction[a]	1.241	1	.265		
Likelihood Ratio	2.443	1	.118		
Fisher's Exact Test				.134	.134
Linear-by-Linear Association	2.628	1	.105		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.45.

ALS Patient * Regular Alcohol

Crosstab

			Regular Alcohol		
			No	Yes	Total
ALS Patient	No	Count	21	12	33
		Expected Count	22.6	10.4	33.0
		% within ALS Patient	63.6%	36.4%	100.0%
		% within Regular Alcohol	80.8%	100.0%	86.8%
		% of Total	55.3%	31.6%	86.8%
	Yes	Count	5	0	5
		Expected Count	3.4	1.6	5.0
		% within ALS Patient	100.0%	.0%	100.0%
		% within Regular Alcohol	19.2%	.0%	13.2%
		% of Total	13.2%	.0%	13.2%
Total		Count	26	12	38
		Expected Count	26.0	12.0	38.0
		% within ALS Patient	68.4%	31.6%	100.0%
		% within Regular Alcohol	100.0%	100.0%	100.0%
		% of Total	68.4%	31.6%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.657[b]	1	.103		
Continuity Correction[a]	1.241	1	.265		
Likelihood Ratio	4.136	1	.042		
Fisher's Exact Test				.158	.131
Linear-by-Linear Association	2.587	1	.108		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.58.

ALS Patient * Acting Experience

Crosstab

			Acting Experience		Total
			No	Yes	
ALS Patient	No	Count	30	3	33
		Expected Count	30.4	2.6	33.0
		% within ALS Patient	90.9%	9.1%	100.0%
		% within Acting Experience	85.7%	100.0%	86.8%
		% of Total	78.9%	7.9%	86.8%
	Yes	Count	5	0	5
		Expected Count	4.6	.4	5.0
		% within ALS Patient	100.0%	.0%	100.0%
		% within Acting Experience	14.3%	.0%	13.2%
		% of Total	13.2%	.0%	13.2%
Total		Count	35	3	38
		Expected Count	35.0	3.0	38.0
		% within ALS Patient	92.1%	7.9%	100.0%
		% within Acting Experience	100.0%	100.0%	100.0%
		% of Total	92.1%	7.9%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.494[b]	1	.482		
Continuity Correction[a]	.000	1	1.000		
Likelihood Ratio	.885	1	.347		
Fisher's Exact Test				1.000	.647
Linear-by-Linear Association	.481	1	.488		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 3 cells (75.0%) have expected count less than 5. The minimum expected count is .39.

ALS Patient * Meditation Experience

Crosstab

			Meditation Experience		
			No	Yes	Total
ALS Patient	No	Count	31	2	33
		Expected Count	26.9	6.1	33.0
		% within ALS Patient	93.9%	6.1%	100.0%
		% within Meditation Experience	100.0%	28.6%	86.8%
		% of Total	81.6%	5.3%	86.8%
	Yes	Count	0	5	5
		Expected Count	4.1	.9	5.0
		% within ALS Patient	.0%	100.0%	100.0%
		% within Meditation Experience	.0%	71.4%	13.2%
		% of Total	.0%	13.2%	13.2%
Total		Count	31	7	38
		Expected Count	31.0	7.0	38.0
		% within ALS Patient	81.6%	18.4%	100.0%
		% within Meditation Experience	100.0%	100.0%	100.0%
		% of Total	81.6%	18.4%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	25.498[b]	1	.000		
Continuity Correction[a]	19.630	1	.000		
Likelihood Ratio	21.217	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	24.827	1	.000		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is .92.

ALS Patient * Dexterity

Crosstab

			Dexterity		
			No	Yes	Total
ALS Patient	No	Count	13	20	33
		Expected Count	13.0	20.0	33.0
		% within ALS Patient	39.4%	60.6%	100.0%
		% within Dexterity	86.7%	87.0%	86.8%
		% of Total	34.2%	52.6%	86.8%
	Yes	Count	2	3	5
		Expected Count	2.0	3.0	5.0
		% within ALS Patient	40.0%	60.0%	100.0%
		% within Dexterity	13.3%	13.0%	13.2%
		% of Total	5.3%	7.9%	13.2%
Total		Count	15	23	38
		Expected Count	15.0	23.0	38.0
		% within ALS Patient	39.5%	60.5%	100.0%
		% within Dexterity	100.0%	100.0%	100.0%
		% of Total	39.5%	60.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.001[b]	1	.979		
Continuity Correction[a]	.000	1	1.000		
Likelihood Ratio	.001	1	.979		
Fisher's Exact Test				1.000	.668
Linear-by-Linear Association	.001	1	.980		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.97.

ALS Patient * Play(ed) Sports

Crosstab

			Play Sports		Total
			No	Yes	
ALS Patient	No	Count	6	27	33
		Expected Count	6.1	26.9	33.0
		% within ALS Patient	18.2%	81.8%	100.0%
		% within Play Sports	85.7%	87.1%	86.8%
		% of Total	15.8%	71.1%	86.8%
	Yes	Count	1	4	5
		Expected Count	.9	4.1	5.0
		% within ALS Patient	20.0%	80.0%	100.0%
		% within Play Sports	14.3%	12.9%	13.2%
		% of Total	2.6%	10.5%	13.2%
Total		Count	7	31	38
		Expected Count	7.0	31.0	38.0
		% within ALS Patient	18.4%	81.6%	100.0%
		% within Play Sports	100.0%	100.0%	100.0%
		% of Total	18.4%	81.6%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.010[b]	1	.922		
Continuity Correction[a]	.000	1	1.000		
Likelihood Ratio	.009	1	.923		
Fisher's Exact Test				1.000	.661
Linear-by-Linear Association	.009	1	.923		
N of Valid Cases	38				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is .92.

ALS Patient * First-Person Shooter Games

Crosstab

			First-Person Shooter Games			Total
			None	Some	Extensive	
ALS Patient	No	Count	13	13	7	33
		Expected Count	14.8	11.3	6.9	33.0
		% within ALS Patient	39.4%	39.4%	21.2%	100.0%
		% within First-Person Shooter Games	76.5%	100.0%	87.5%	86.8%
		% of Total	34.2%	34.2%	18.4%	86.8%
	Yes	Count	4	0	1	5
		Expected Count	2.2	1.7	1.1	5.0
		% within ALS Patient	80.0%	.0%	20.0%	100.0%
		% within First-Person Shooter Games	23.5%	.0%	12.5%	13.2%
		% of Total	10.5%	.0%	2.6%	13.2%
Total		Count	17	13	8	38
		Expected Count	17.0	13.0	8.0	38.0
		% within ALS Patient	44.7%	34.2%	21.1%	100.0%
		% within First-Person Shooter Games	100.0%	100.0%	100.0%	100.0%
		% of Total	44.7%	34.2%	21.1%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.573[a]	2	.168
Likelihood Ratio	5.014	2	.082
Linear-by-Linear Association	1.229	1	.268
N of Valid Cases	38		

a. 3 cells (50.0%) have expected count less than 5. The minimum expected count is 1.05.

ALS Patient * Adventure Games

Crosstab

			Adventure Games			
			None	Some	Extensive	Total
ALS Patient	No	Count	15	15	3	33
		Expected Count	16.5	13.9	2.6	33.0
		% within ALS Patient	45.5%	45.5%	9.1%	100.0%
		% within Adventure Games	78.9%	93.8%	100.0%	86.8%
		% of Total	39.5%	39.5%	7.9%	86.8%
	Yes	Count	4	1	0	5
		Expected Count	2.5	2.1	.4	5.0
		% within ALS Patient	80.0%	20.0%	.0%	100.0%
		% within Adventure Games	21.1%	6.3%	.0%	13.2%
		% of Total	10.5%	2.6%	.0%	13.2%
Total		Count	19	16	3	38
		Expected Count	19.0	16.0	3.0	38.0
		% within ALS Patient	50.0%	42.1%	7.9%	100.0%
		% within Adventure Games	100.0%	100.0%	100.0%	100.0%
		% of Total	50.0%	42.1%	7.9%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.159[a]	2	.340
Likelihood Ratio	2.555	2	.279
Linear-by-Linear Association	2.004	1	.157
N of Valid Cases	38		

a. 4 cells (66.7%) have expected count less than 5. The minimum expected count is .39.

ALS Patient * Puzzle Games

Crosstab

			Puzzle Games			Total
			None	Some	Extensive	
ALS Patient	No	Count	9	15	9	33
		Expected Count	8.7	14.8	9.6	33.0
		% within ALS Patient	27.3%	45.5%	27.3%	100.0%
		% within Puzzle Games	90.0%	88.2%	81.8%	86.8%
		% of Total	23.7%	39.5%	23.7%	86.8%
	Yes	Count	1	2	2	5
		Expected Count	1.3	2.2	1.4	5.0
		% within ALS Patient	20.0%	40.0%	40.0%	100.0%
		% within Puzzle Games	10.0%	11.8%	18.2%	13.2%
		% of Total	2.6%	5.3%	5.3%	13.2%
Total		Count	10	17	11	38
		Expected Count	10.0	17.0	11.0	38.0
		% within ALS Patient	26.3%	44.7%	28.9%	100.0%
		% within Puzzle Games	100.0%	100.0%	100.0%	100.0%
		% of Total	26.3%	44.7%	28.9%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	.359[a]	2	.836
Likelihood Ratio	.345	2	.842
Linear-by-Linear Association	.306	1	.580
N of Valid Cases	38		

a. 3 cells (50.0%) have expected count less than 5. The minimum expected count is 1.32.

ALS Patient * Strategy Games

Crosstab

			Strategy Games			
			None	Some	Extensive	Total
ALS Patient	No	Count	19	6	8	33
		Expected Count	20.0	5.2	7.8	33.0
		% within ALS Patient	57.6%	18.2%	24.2%	100.0%
		% within Strategy Games	82.6%	100.0%	88.9%	86.8%
		% of Total	50.0%	15.8%	21.1%	86.8%
	Yes	Count	4	0	1	5
		Expected Count	3.0	.8	1.2	5.0
		% within ALS Patient	80.0%	.0%	20.0%	100.0%
		% within Strategy Games	17.4%	.0%	11.1%	13.2%
		% of Total	10.5%	.0%	2.6%	13.2%
Total		Count	23	6	9	38
		Expected Count	23.0	6.0	9.0	38.0
		% within ALS Patient	60.5%	15.8%	23.7%	100.0%
		% within Strategy Games	100.0%	100.0%	100.0%	100.0%
		% of Total	60.5%	15.8%	23.7%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	1.303[a]	2	.521
Likelihood Ratio	2.060	2	.357
Linear-by-Linear Association	.426	1	.514
N of Valid Cases	38		

a. 3 cells (50.0%) have expected count less than 5. The minimum expected count is .79.

ALS Patient * Rhythm Games

Crosstab

			Rhythm Games			
			None	Some	Extensive	Total
ALS Patient	No	Count	23	7	3	33
		Expected Count	24.3	6.1	2.6	33.0
		% within ALS Patient	69.7%	21.2%	9.1%	100.0%
		% within Rhythm Games	82.1%	100.0%	100.0%	86.8%
		% of Total	60.5%	18.4%	7.9%	86.8%
	Yes	Count	5	0	0	5
		Expected Count	3.7	.9	.4	5.0
		% within ALS Patient	100.0%	.0%	.0%	100.0%
		% within Rhythm Games	17.9%	.0%	.0%	13.2%
		% of Total	13.2%	.0%	.0%	13.2%
Total		Count	28	7	3	38
		Expected Count	28.0	7.0	3.0	38.0
		% within ALS Patient	73.7%	18.4%	7.9%	100.0%
		% within Rhythm Games	100.0%	100.0%	100.0%	100.0%
		% of Total	73.7%	18.4%	7.9%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.056[a]	2	.358
Likelihood Ratio	3.316	2	.190
Linear-by-Linear Association	1.713	1	.191
N of Valid Cases	38		

a. 4 cells (66.7%) have expected count less than 5. The minimum expected count is .39.

ALS Patient * Role-Playing Games

Crosstab

			Role-Playing Games			Total
			None	Some	Extensive	
ALS Patient	No	Count	19	8	6	33
		Expected Count	20.8	6.9	5.2	33.0
		% within ALS Patient	57.6%	24.2%	18.2%	100.0%
		% within Role-Playing Games	79.2%	100.0%	100.0%	86.8%
		% of Total	50.0%	21.1%	15.8%	86.8%
	Yes	Count	5	0	0	5
		Expected Count	3.2	1.1	.8	5.0
		% within ALS Patient	100.0%	.0%	.0%	100.0%
		% within Role-Playing Games	20.8%	.0%	.0%	13.2%
		% of Total	13.2%	.0%	.0%	13.2%
Total		Count	24	8	6	38
		Expected Count	24.0	8.0	6.0	38.0
		% within ALS Patient	63.2%	21.1%	15.8%	100.0%
		% within Role-Playing Games	100.0%	100.0%	100.0%	100.0%
		% of Total	63.2%	21.1%	15.8%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.359[a]	2	.187
Likelihood Ratio	5.029	2	.081
Linear-by-Linear Association	2.748	1	.097
N of Valid Cases	38		

a. 3 cells (50.0%) have expected count less than 5. The minimum expected count is .79.

ALS Patient * Simulations

Crosstab

			Simulations			
			None	Some	Extensive	Total
ALS Patient	No	Count	18	12	3	33
		Expected Count	19.1	10.4	3.5	33.0
		% within ALS Patient	54.5%	36.4%	9.1%	100.0%
		% within Simulations	81.8%	100.0%	75.0%	86.8%
		% of Total	47.4%	31.6%	7.9%	86.8%
	Yes	Count	4	0	1	5
		Expected Count	2.9	1.6	.5	5.0
		% within ALS Patient	80.0%	.0%	20.0%	100.0%
		% within Simulations	18.2%	.0%	25.0%	13.2%
		% of Total	10.5%	.0%	2.6%	13.2%
Total		Count	22	12	4	38
		Expected Count	22.0	12.0	4.0	38.0
		% within ALS Patient	57.9%	31.6%	10.5%	100.0%
		% within Simulations	100.0%	100.0%	100.0%	100.0%
		% of Total	57.9%	31.6%	10.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.795[a]	2	.247
Likelihood Ratio	4.232	2	.121
Linear-by-Linear Association	.195	1	.659
N of Valid Cases	38		

a. 4 cells (66.7%) have expected count less than 5. The minimum expected count is .53.

ALS Patient * SportGames

Crosstab

			SportGames			Total
			None	Some	Extensive	
ALS Patient	No	Count	22	7	4	33
		Expected Count	22.6	6.9	3.5	33.0
		% within ALS Patient	66.7%	21.2%	12.1%	100.0%
		% within SportGames	84.6%	87.5%	100.0%	86.8%
		% of Total	57.9%	18.4%	10.5%	86.8%
	Yes	Count	4	1	0	5
		Expected Count	3.4	1.1	.5	5.0
		% within ALS Patient	80.0%	20.0%	.0%	100.0%
		% within SportGames	15.4%	12.5%	.0%	13.2%
		% of Total	10.5%	2.6%	.0%	13.2%
Total		Count	26	8	4	38
		Expected Count	26.0	8.0	4.0	38.0
		% within ALS Patient	68.4%	21.1%	10.5%	100.0%
		% within SportGames	100.0%	100.0%	100.0%	100.0%
		% of Total	68.4%	21.1%	10.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	.722[a]	2	.697
Likelihood Ratio	1.240	2	.538
Linear-by-Linear Association	.603	1	.437
N of Valid Cases	38		

a. 4 cells (66.7%) have expected count less than 5. The minimum expected count is .53.

ALS Patient * ComputerUse

Crosstab

			ComputerUse			
			Hardly Ever	A Little	Extensively	Total
ALS Patient	No	Count	0	4	29	33
		Expected Count	.9	4.3	27.8	33.0
		% within ALS Patient	.0%	12.1%	87.9%	100.0%
		% within ComputerUse	.0%	80.0%	90.6%	86.8%
		% of Total	.0%	10.5%	76.3%	86.8%
	Yes	Count	1	1	3	5
		Expected Count	.1	.7	4.2	5.0
		% within ALS Patient	20.0%	20.0%	60.0%	100.0%
		% within ComputerUse	100.0%	20.0%	9.4%	13.2%
		% of Total	2.6%	2.6%	7.9%	13.2%
Total		Count	1	5	32	38
		Expected Count	1.0	5.0	32.0	38.0
		% within ALS Patient	2.6%	13.2%	84.2%	100.0%
		% within ComputerUse	100.0%	100.0%	100.0%	100.0%
		% of Total	2.6%	13.2%	84.2%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	7.206[a]	2	.027
Likelihood Ratio	4.676	2	.097
Linear-by-Linear Association	4.776	1	.029
N of Valid Cases	38		

a. 5 cells (83.3%) have expected count less than 5. The minimum expected count is .13.

ALS Patient * Skin Color

Crosstab

			Skin Color				Total
			White	LightBrown	MediumBrown	DarkBrown	
ALS Patient	No	Count	14	12	3	4	33
		Expected Count	15.6	11.3	2.6	3.5	33.0
		% within ALS Patient	42.4%	36.4%	9.1%	12.1%	100.0%
		% within Skin Color	77.8%	92.3%	100.0%	100.0%	86.8%
		% of Total	36.8%	31.6%	7.9%	10.5%	86.8%
	Yes	Count	4	1	0	0	5
		Expected Count	2.4	1.7	.4	.5	5.0
		% within ALS Patient	80.0%	20.0%	.0%	.0%	100.0%
		% within Skin Color	22.2%	7.7%	.0%	.0%	13.2%
		% of Total	10.5%	2.6%	.0%	.0%	13.2%
Total		Count	18	13	3	4	38
		Expected Count	18.0	13.0	3.0	4.0	38.0
		% within ALS Patient	47.4%	34.2%	7.9%	10.5%	100.0%
		% within Skin Color	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	47.4%	34.2%	7.9%	10.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.695[a]	3	.441
Likelihood Ratio	3.472	3	.324
Linear-by-Linear Association	2.262	1	.133
N of Valid Cases	38		

a. 6 cells (75.0%) have expected count less than 5. The minimum expected count is .39.

ALS Patient * Hair Color

Crosstab

			Hair Color				Total
			Blond/None	Brown	Black	Gray	
ALS Patient	No	Count	1	13	18	1	33
		Expected Count	.9	14.8	15.6	1.7	33.0
		% within ALS Patient	3.0%	39.4%	54.5%	3.0%	100.0%
		% within Hair Color	100.0%	76.5%	100.0%	50.0%	86.8%
		% of Total	2.6%	34.2%	47.4%	2.6%	86.8%
	Yes	Count	0	4	0	1	5
		Expected Count	.1	2.2	2.4	.3	5.0
		% within ALS Patient	.0%	80.0%	.0%	20.0%	100.0%
		% within Hair Color	.0%	23.5%	.0%	50.0%	13.2%
		% of Total	.0%	10.5%	.0%	2.6%	13.2%
Total		Count	1	17	18	2	38
		Expected Count	1.0	17.0	18.0	2.0	38.0
		% within ALS Patient	2.6%	44.7%	47.4%	5.3%	100.0%
		% within Hair Color	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	2.6%	44.7%	47.4%	5.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	6.855[a]	3	.077
Likelihood Ratio	8.270	3	.041
Linear-by-Linear Association	.322	1	.570
N of Valid Cases	38		

a. 6 cells (75.0%) have expected count less than 5. The minimum expected count is .13.

ALS Patient * Hair Texture

Crosstab

			Hair Texture			
			None	Straight	Curly	Total
ALS Patient	No	Count	1	20	12	33
		Expected Count	.9	19.1	13.0	33.0
		% within ALS Patient	3.0%	60.6%	36.4%	100.0%
		% within Hair Texture	100.0%	90.9%	80.0%	86.8%
		% of Total	2.6%	52.6%	31.6%	86.8%
	Yes	Count	0	2	3	5
		Expected Count	.1	2.9	2.0	5.0
		% within ALS Patient	.0%	40.0%	60.0%	100.0%
		% within Hair Texture	.0%	9.1%	20.0%	13.2%
		% of Total	.0%	5.3%	7.9%	13.2%
Total		Count	1	22	15	38
		Expected Count	1.0	22.0	15.0	38.0
		% within ALS Patient	2.6%	57.9%	39.5%	100.0%
		% within Hair Texture	100.0%	100.0%	100.0%	100.0%
		% of Total	2.6%	57.9%	39.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	1.085[a]	2	.581
Likelihood Ratio	1.177	2	.555
Linear-by-Linear Association	1.054	1	.305
N of Valid Cases	38		

a. 4 cells (66.7%) have expected count less than 5. The minimum expected count is .13.

Appendix K: Test-Wise Regression Results

Age

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.456[a]	.208	.186	.143095

a. Predictors: (Constant), Age

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.681	.074		9.249	.000
	Age	-5.47E-03	.002	-.456	-3.073	.004

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.503[a]	.253	.232	.190224

a. Predictors: (Constant), Age

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.679	.098		6.935	.000
	Age	-8.27E-03	.002	-.503	-3.493	.001

a. Dependent Variable: GSR Success

Sex

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.251[a]	.063	.037	.155618

a. Predictors: (Constant), Sex

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.412	.043		9.542	.000
	Sex	8.285E-02	.053	.251	1.557	.128

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.420[a]	.176	.153	.199804

a. Predictors: (Constant), Sex

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.230	.055		4.145	.000
	Sex	.189	.068	.420	2.773	.009

a. Dependent Variable: GSR Success

Smoking Experience

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.031[a]	.001	-.027	.160696

a. Predictors: (Constant), Smoker

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.469	.030		15.451	.000
	Smoker	-1.09E-02	.059	-.031	-.184	.855

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.012[a]	.000	-.028	.220099

a. Predictors: (Constant), Smoker

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.356	.042		8.557	.000
	Smoker	-5.91E-03	.081	-.012	-.073	.942

a. Dependent Variable: GSR Success

Affective Drugs

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.154[a]	.024	-.003	.158852

a. Predictors: (Constant), Drugs

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.478	.029		16.748	.000
	Drugs	-6.22E-02	.066	-.154	-.936	.356

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.203[a]	.041	.014	.215541

a. Predictors: (Constant), Drugs

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.375	.039		9.687	.000
	Drugs	-.112	.090	-.203	-1.243	.222

a. Dependent Variable: GSR Success

Regular Caffeine Consumption

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.356[a]	.127	.103	.150235

a. Predictors: (Constant), Regular Caffeine

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.554	.045		12.223	.000
	Regular Caffeine	-.123	.054	-.356	-2.286	.028

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.057[a]	.003	-.024	.219757

a. Predictors: (Constant), Regular Caffeine

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.335	.066		5.059	.000
	Regular Caffeine	2.692E-02	.079	.057	.342	.734

a. Dependent Variable: GSR Success

Regular Alcohol Consumption

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.093[a]	.009	-.019	.160080

a. Predictors: (Constant), Regular Alcohol

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.476	.031		15.169	.000
	Regular Alcohol	-3.12E-02	.056	-.093	-.558	.580

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.355[a]	.126	.102	.205744

a. Predictors: (Constant), Regular Alcohol

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.303	.040		7.500	.000
	Regular Alcohol	.164	.072	.355	2.281	.029

a. Dependent Variable: GSR Success

Acting Experience

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.115[a]	.013	-.014	.159707

a. Predictors: (Constant), Acting Experience

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.461	.027		17.081	.000
	Acting Experience	6.668E-02	.096	.115	.694	.492

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.256[a]	.066	.040	.212752

a. Predictors: (Constant), Acting Experience

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.370	.036		10.301	.000
	Acting Experience	-.204	.128	-.256	-1.592	.120

a. Dependent Variable: GSR Success

Meditation Experience

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.040[a]	.002	-.026	.160646

a. Predictors: (Constant), Meditation Experience

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.469	.029		16.266	.000
	Meditation Experience	-1.60E-02	.067	-.040	-.238	.813

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.467[a]	.218	.196	.194656

a. Predictors: (Constant), Meditation Experience

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.402	.035		11.495	.000
	Meditation Experience	-.258	.081	-.467	-3.167	.003

a. Dependent Variable: GSR Success

Dexterity

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.058[a]	.003	-.024	.160499

a. Predictors: (Constant), Dexterity

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.455	.041		10.981	.000
	Dexterity	1.866E-02	.053	.058	.350	.728

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.238[a]	.057	.030	.213790

a. Predictors: (Constant), Dexterity

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.291	.055		5.276	.000
	Dexterity	.104	.071	.238	1.470	.150

a. Dependent Variable: GSR Success

Play(ed) Sports

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.097[a]	.009	-.018	.160019

a. Predictors: (Constant), Play Sports

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.435	.060		7.184	.000
	Play Sports	3.903E-02	.067	.097	.583	.564

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.258[a]	.066	.041	.212671

a. Predictors: (Constant), Play Sports

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.238	.080		2.962	.005
	Play Sports	.143	.089	.258	1.601	.118

a. Dependent Variable: GSR Success

Athleticism/Physical Activity

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.093[a]	.009	-.019	.160072

a. Predictors: (Constant), Athleticism

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.438	.057		7.741	.000
	Athleticism	8.944E-03	.016	.093	.562	.578

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.131[a]	.017	-.010	.218228

a. Predictors: (Constant), Athleticism

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.300	.077		3.890	.000
	Athleticism	1.717E-02	.022	.131	.791	.434

a. Dependent Variable: GSR Success

Hours Training with Biometric Interfaces

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.171[a]	.029	.002	.158404

a. Predictors: (Constant), Biometric Training

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.455	.028		16.271	.000
	Biometric Training	1.063E-02	.010	.171	1.041	.305

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.096[a]	.009	-.018	.219092

a. Predictors: (Constant), Biometric Training

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.363	.039		9.392	.000
	Biometric Training	-8.19E-03	.014	-.096	-.580	.565

a. Dependent Variable: GSR Success

Video-Game Experience: First-Person Shooter Games

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.249[a]	.062	.036	.155711

a. Predictors: (Constant), First-Person Shooter Games

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.378	.063		6.024	.000
	First-Person Shooter Games	5.022E-02	.033	.249	1.542	.132

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.342[a]	.117	.093	.206821

a. Predictors: (Constant), First-Person Shooter Games

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.188	.083		2.253	.030
	First-Person Shooter Games	9.452E-02	.043	.342	2.186	.035

a. Dependent Variable: GSR Success

Video-Game Experience: Adventure Games

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.239[a]	.057	.031	.156127

a. Predictors: (Constant), Adventure Games

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.373	.068		5.491	.000
	Adventure Games	5.892E-02	.040	.239	1.474	.149

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.163[a]	.027	.000	.217155

a. Predictors: (Constant), Adventure Games

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.267	.095		2.825	.008
	Adventure Games	5.525E-02	.056	.163	.994	.327

a. Dependent Variable: GSR Success

Video-Game Experience: Puzzle Games

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.213[a]	.046	.019	.157066

a. Predictors: (Constant), Puzzle Games

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.375	.074		5.070	.000
	Puzzle Games	4.496E-02	.034	.213	1.311	.198

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.178[a]	.032	.005	.216601

a. Predictors: (Constant), Puzzle Games

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.250	.102		2.453	.019
	Puzzle Games	5.132E-02	.047	.178	1.085	.285

a. Dependent Variable: GSR Success

Video-Game Experience: Strategy Games

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.152[a]	.023	-.004	.158912

a. Predictors: (Constant), Strategy Games

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.420	.056		7.466	.000
	Strategy Games	2.824E-02	.031	.152	.921	.363

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.422[a]	.178	.155	.199597

a. Predictors: (Constant), Strategy Games

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.179	.071		2.532	.016
	Strategy Games	.107	.039	.422	2.790	.008

a. Dependent Variable: GSR Success

Video-Game Experience: Rhythm Games

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.174[a]	.030	.003	.158332

a. Predictors: (Constant), Rhythm Games

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.407	.061		6.643	.000
	Rhythm Games	4.388E-02	.042	.174	1.057	.297

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.089[a]	.008	-.020	.219239

a. Predictors: (Constant), Rhythm Games

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.313	.085		3.685	.001
	Rhythm Games	3.085E-02	.057	.089	.537	.595

a. Dependent Variable: GSR Success

Video-Game Experience: Role-Playing Games

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.224[a]	.050	.024	.156705

a. Predictors: (Constant), Role-Playing Games

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.395	.058		6.871	.000
	Role-Playing Games	4.653E-02	.034	.224	1.376	.177

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.453[a]	.205	.183	.196204

a. Predictors: (Constant), Role-Playing Games

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.157	.072		2.182	.036
	Role-Playing Games	.129	.042	.453	3.051	.004

a. Dependent Variable: GSR Success

Video-Game Experience: Simulation Games

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.206[a]	.043	.016	.157315

a. Predictors: (Constant), Simulations

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.394	.063		6.264	.000
	Simulations	4.760E-02	.038	.206	1.265	.214

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.368[a]	.135	.111	.204673

a. Predictors: (Constant), Simulations

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.177	.082		2.163	.037
	Simulations	.116	.049	.368	2.374	.023

a. Dependent Variable: GSR Success

Video-Game Experience: Sports Games

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.221[a]	.049	.022	.156803

a. Predictors: (Constant), SportGames

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.394	.059		6.630	.000
	SportGames	5.127E-02	.038	.221	1.358	.183

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.308[a]	.095	.070	.209394

a. Predictors: (Constant), SportGames

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.215	.079		2.714	.010
	SportGames	9.799E-02	.050	.308	1.944	.060

a. Dependent Variable: GSR Success

Computer Use

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.120[a]	.014	-.013	.159615

a. Predictors: (Constant), ComputerUse

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.349	.164		2.130	.040
	ComputerUse	4.160E-02	.057	.120	.724	.474

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.146[a]	.021	-.006	.217754

a. Predictors: (Constant), ComputerUse

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.159	.224		.710	.482
	ComputerUse	6.948E-02	.078	.146	.886	.382

a. Dependent Variable: GSR Success

Motor Control

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.005[a]	.000	-.028	.160770

a. Predictors: (Constant), Yrs with Paralysis

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.466	.027		17.209	.000
	Yrs with Paralysis	1.923E-04	.006	.005	.030	.976

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.151[a]	.023	-.004	.217584

a. Predictors: (Constant), Yrs with Paralysis

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.363	.037		9.914	.000
	Yrs with Paralysis	-8.03E-03	.009	-.151	-.918	.365

a. Dependent Variable: GSR Success

Skin Color

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.043[a]	.002	-.026	.160622

a. Predictors: (Constant), Skin Color

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.479	.055		8.658	.000
	Skin Color	-6.97E-03	.027	-.043	-.259	.797

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.386[a]	.149	.125	.203043

a. Predictors: (Constant), Skin Color

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.509	.070		7.282	.000
	Skin Color	-8.53E-02	.034	-.386	-2.512	.017

a. Dependent Variable: GSR Success

Hair Color

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.074[a]	.005	-.022	.160332

a. Predictors: (Constant), Hair Color

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.513	.108		4.770	.000
	Hair Color	-1.82E-02	.041	-.074	-.445	.659

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.367[a]	.134	.110	.204789

a. Predictors: (Constant), Hair Color

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.669	.137		4.875	.000
	Hair Color	-.123	.052	-.367	-2.364	.024

a. Dependent Variable: GSR Success

Hair Texture

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.264[a]	.070	.044	.155063

a. Predictors: (Constant), Hair Texture

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.283	.114		2.476	.018
	Hair Texture	7.738E-02	.047	.264	1.643	.109

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.362[a]	.131	.107	.205229

a. Predictors: (Constant), Hair Texture

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.698	.151		4.611	.000
	Hair Texture	-.145	.062	-.362	-2.326	.026

a. Dependent Variable: GSR Success

Years of Education

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.352[a]	.124	.100	.150458

a. Predictors: (Constant), Yrs Education

b. Dependent Variable: fNIR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	8.460E-03	.204		.041	.967
	Yrs Education	2.681E-02	.012	.352	2.259	.030

a. Dependent Variable: fNIR Success

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.030[a]	.001	-.027	.220016

a. Predictors: (Constant), Yrs Education

b. Dependent Variable: GSR Success

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.408	.299		1.365	.181
	Yrs Education	-3.12E-03	.017	-.030	-.180	.858

a. Dependent Variable: GSR Success

Appendix L: Correlations

Correlations

			fNIR Success	GSR Success	Athleticism	Yrs with Paralysis	Yrs Education	Age
Spearman's rho	fNIR Success	Correlation Coefficient	1.000	.242	.096	-.052	.379**	-.438**
		Sig. (1-tailed)	.	.071	.283	.378	.009	.003
		N	38	38	38	38	38	38
	GSR Success	Correlation Coefficient	.242	1.000	.119	-.206	.034	-.496**
		Sig. (1-tailed)	.071	.	.238	.107	.420	.001
		N	38	38	38	38	38	38
	Athleticism	Correlation Coefficient	.096	.119	1.000	-.387**	.376**	-.392**
		Sig. (1-tailed)	.283	.238	.	.008	.010	.007
		N	38	38	38	38	38	38
	Yrs with Paralysis	Correlation Coefficient	-.052	-.206	-.387**	1.000	-.167	.222
		Sig. (1-tailed)	.378	.107	.008	.	.158	.090
		N	38	38	38	38	38	38
	Yrs Education	Correlation Coefficient	.379**	.034	.376**	-.167	1.000	-.261
		Sig. (1-tailed)	.009	.420	.010	.158	.	.057
		N	38	38	38	38	38	38
	Age	Correlation Coefficient	-.438**	-.496**	-.392**	.222	-.261	1.000
		Sig. (1-tailed)	.003	.001	.007	.090	.057	.
		N	38	38	38	38	38	38

**. Correlation is significant at the .01 level (1-tailed).

Correlations

			First-Person Shooter Games	Adventure Games	Puzzle Games	Strategy Games	Rhythm Games	Role-Playing Games	Simulations	SportGames
Spearman's rho	First-Person Shooter Games	Correlation Coefficient	1.000	.825**	.637**	.824**	.438**	.641**	.678**	.571**
		Sig. (1-tailed)	.	.000	.000	.000	.003	.000	.000	.000
		N	38	38	38	38	38	38	38	38
	Adventure Games	Correlation Coefficient	.825**	1.000	.510**	.724**	.477**	.599**	.628**	.473**
		Sig. (1-tailed)	.000	.	.001	.000	.001	.000	.000	.001
		N	38	38	38	38	38	38	38	38
	Puzzle Games	Correlation Coefficient	.637**	.510**	1.000	.461**	.483**	.466**	.557**	.175
		Sig. (1-tailed)	.000	.001	.	.002	.001	.002	.000	.147
		N	38	38	38	38	38	38	38	38
	Strategy Games	Correlation Coefficient	.824**	.724**	.461**	1.000	.302*	.716**	.617**	.653**
		Sig. (1-tailed)	.000	.000	.002	.	.033	.000	.000	.000
		N	38	38	38	38	38	38	38	38
	Rhythm Games	Correlation Coefficient	.438**	.477**	.483**	.302*	1.000	.433**	.367*	-.086
		Sig. (1-tailed)	.003	.001	.001	.033	.	.003	.012	.304
		N	38	38	38	38	38	38	38	38
	Role-Playing Games	Correlation Coefficient	.641**	.599**	.466**	.716**	.433**	1.000	.567**	.340*
		Sig. (1-tailed)	.000	.000	.002	.000	.003	.	.000	.018
		N	38	38	38	38	38	38	38	38
	Simulations	Correlation Coefficient	.678**	.628**	.557**	.617**	.367*	.567**	1.000	.587**
		Sig. (1-tailed)	.000	.000	.000	.000	.012	.000	.	.000
		N	38	38	38	38	38	38	38	38
	SportGames	Correlation Coefficient	.571**	.473**	.175	.653**	-.086	.340*	.587**	1.000
		Sig. (1-tailed)	.000	.001	.147	.000	.304	.018	.000	.
		N	38	38	38	38	38	38	38	38

**. Correlation is significant at the .01 level (1-tailed).

*. Correlation is significant at the .05 level (1-tailed).

Correlations

			Skin Color	Hair Color	Hair Texture
Spearman's rho	Skin Color	Correlation Coefficient	1.000	.705**	.384**
		Sig. (1-tailed)	.	.000	.009
		N	38	38	38
	Hair Color	Correlation Coefficient	.705**	1.000	.426**
		Sig. (1-tailed)	.000	.	.004
		N	38	38	38
	Hair Texture	Correlation Coefficient	.384**	.426**	1.000
		Sig. (1-tailed)	.009	.004	.
		N	38	38	38

**. Correlation is significant at the .01 level (1-tailed).

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9. Curriculum Vitae

Biographical Details

Name:	Adriane B. Randolph
Birthplace:	Albany, GA USA, April 29, 1977
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Education

2007	Doctor of Philosophy (Business Administration – CIS), Georgia State University
1999	Bachelor of Science (Major – Systems Engineering), University of Virginia

Work Experience

1998 – 1999	Capstone Consultant, Dominion Semiconductor, Manassas, VA
1999 – 2002	Analyst and Consultant, Accenture, Reston, VA
2002 – 2007	Graduate Research Assistant to Melody Moore Jackson, Georgia State University, Atlanta, GA
2003 – 2004	Graduate Teaching Assistant, Georgia State University, Atlanta, GA
2004 – 2007	Visiting Researcher, Georgia Institute of Technology, Atlanta, GA
August 2007	Assistant Professor of Business Information Systems, Kennesaw State University, Kennesaw, GA

Refereed Publications

1. Randolph, Adriane B., Karmakar, Saurav, Moore Jackson, Melody, "Toward Predicting Control of a Brain-Computer Interface," *Proceedings of the International Conference on Information Systems (ICIS)*, Milwaukee, December 10-14, 2006.
2. Randolph, Adriane B., and Hubona, Geoffrey S., "Organizational and Individual Acceptance of Assistive Interfaces and Technologies", Galletta, Dennis, and Ping Zhang, eds. Human-Computer Interaction and Management Information Systems - Applications. *Advances in Management Information Systems (AMIS)*, Volume 5. Armonk, NY: M. E. Sharpe, Inc., 2006.
3. Moore, Melody M., Storey, Veda C., Randolph, Adriane B., "User Profiles for Facilitating Conversations with Locked-in Users," *Proceedings of the International Conference on Information Systems (ICIS)*, Las Vegas, pp. 11-24, December 10-14, 2005.
4. Randolph, Adriane B., McCampbell, Luke A., Moore, Melody M., and Mason, Steven G., "Controllability of Galvanic Skin Response," *Proceedings of the International Conference on Human-Computer Interaction (HCII)*, Las Vegas, July 22-27, 2005.

5. Moore, Melody M., Allison, Brendan Z., and Davis (Randolph), Adriane B. "Brain-Computer Interfaces," In *Encyclopedia of Human Computer Interaction*, C. Ghaoui (ed.) Idea Group Reference, Hershey, PA, April 2005.
6. Moore, Melody M., Storey, Veda C., Davis (Randolph), Adriane B., and Napier, Nannette, "Deriving User Profiles for Augmentative Communication," *Proceedings of the Americas Conference on Information Systems (AMCIS)*, New York City, NY, pp. 3359-3363, August 6-8, 2004.
7. Davis (Randolph), Adriane B., Moore, Melody M., and Storey, Veda C., "Context Aware Communication for Severely Disabled Users," *Proceedings of the Conference on Universal Usability (CUU)*, Vancouver, B. C. Canada, pp. 106-111, November 10-11, 2003

Awards & Honors

1. Invited to attend *Mentoring in Engineering Academia II, Banff International Research Station (BIRS) Workshop* in Banff, Canada, July 2007
2. Selected for a Georgia State University Dissertation Grant Award, 2007
3. Accepted to Rochester Institute of Technology's *Future Faculty Career Exploration Program* (FFCEP), 2006
4. Accepted to North Carolina State University's *Building the Faculty of the Future Program*, 2006
5. Accepted to the Georgia Institute of Technology's *FOCUS Fellows Program*, 2006
6. Recognized in *The Chancellor's List*, 2005-2006
7. Accepted to the *International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS)* Doctoral Consortium, 2004
8. National Science Foundation Graduate Research Fellowship Award, 2004-2007
9. Southern Regional Education Board (SREB) Doctoral Scholar, 2003-2004
10. Accepted to the *Richard J. Tapia Diversity in Computing* Doctoral Consortium, 2003
11. National Science Foundation Graduate Research Honorable Mention, 2003
12. KPMG Ph.D. Project Doctoral Fellow for Information Systems, 2002-2007
13. Inducted into Tau Beta Pi Engineering Honor Society, 1997
14. Inducted into the Golden Key National Honor Society, 1997

Service

<u>Reviewer at Journals</u>: *Information Systems Journal (ISJ), MIS Quarterly (MISQ), IEEE Computer, IEEE Transactions on Neural Systems and Rehabilitation Engineering (TNSRE), The DATA BASE for Advances in Information Systems*

<u>Reviewer at Conferences</u>: *Americas Conference on Information Systems (AMCIS), Hawaii International Conference on System Sciences (HICSS), International Conference on Information Systems (ICIS), International Federation for Information Processing (IFIP) Working Group 8.2*