Not All Created Equal: Individual-Technology Fit of Brain-Computer Interfaces

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Abstract
This work presents a model stemming from literature on task-technology fit that seeks to match individual user characteristics and features of brain-computer interface technologies with performance to expedite the technology-fit process. The individual-technology fit model is tested with a brain-computer interface based on a control signal called the mu rhythm that is recorded from the motor cortex region. Characteristics from eighty total participants are tested across two different sessions. Performance is measured as a person’s ability to modulate his/her mu rhythm. It appears that the version of software used in recording and interpreting EEGs, instrument playing, being on affective drugs, a person’s sex, and age all play key roles in predicting mu rhythm modulation.

1. Introduction
Spanning information systems 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…” [1, page 1]. 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. However, a gap remains in the effective design of non-traditional assistive technologies, such as brain-computer interfaces (BCIs).

Assistive technology augments the functional capabilities of people with disabilities and without. 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. Brain-computer interfaces use neurophysiological measures for non-muscularly controlled computer applications [2] and can therefore be considered non-traditional assistive technologies. Brain-computer 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 situational disabilities induced by their environment, such as with jet pilots and astronauts subjected to extreme forces, soldiers in hostile territory, and even video gamers [3, 4].

Brain-computer 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 environments. Thus, severely disabled users who are able to control BCI technologies often experience a significant improvement in their quality of life [5].

Unfortunately, the effectiveness of BCIs is limited by the ability of users to provide distinguishable changes in their neurophysiological input, also known as BCI literacy [6], and usability of the provided control interface [7]. Various factors affect this literacy and range from the person’s current fatigue level to physiological makeup [8].

The related field of Neuro-IS has recently evolved by examining how neuroscience methods can inform information systems [9, 10]. Here, information systems can inform neuroscience by examining the match between an individual and BCI technology which is their individual-technology fit (ITF); this ITF can be reflected by the individual’s performance with the BCI technology.

Currently, there is a disparity in goals between researchers and practitioners investigating BCIs; researchers focus more on technology characteristics, and practitioners focus more on user characteristics, resulting in available BCI technologies often being matched to users through trial-and-error [11, 12] and increasing the levels of BCI illiteracy. Unfortunately, this approach can waste valuable time and resources as users sometimes have diminishing abilities or suffer from terminal illnesses. There have been
efforts to characterize the degree of controllability of a BCI by an individual [13, 14] but ties between controllability and an individual’s characteristics are just beginning to be investigated [12, 15-17]. A methodology that ties performance to available BCI technologies based on individual characteristics can greatly expedite the technology-fit process.

This work examines an important consideration for BCI 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. With better means for explaining performance with various BCI 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 Neuro-IS with the use of BCIs 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 BCIs. In addition, these models are not intended to uncover the salient user characteristics necessary for an effective pairing with various BCI technologies. Therefore, this research proposes that: salient individual user characteristics may be identified and modeled in a way that matches with features of brain-computer interface technologies to explain performance.

1.1. Brain-Computer Interfaces

Research in the field of BCIs spans several disciplines including computer science, electrical engineering, cognitive psychology, neuroscience, and information systems. There are a number of different types of BCIs available that vary according to the type of neurophysiological signal recorded, method used for recording, and cognitive tasks employed. Most applications target disabled users who are cognitively intact but have such severely limited mobility that system input through physical movement (using a keyboard, mouse, joystick, switches, or eye-gaze devices) is infeasible. Brain-computer interfaces, therefore, provide non-traditional assistance for controlling computers using neural input.

This work focuses on non-invasive techniques for recording BCI input 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 [18]. Other approaches include 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 and functional near-infrared (fNIR) which also measures oxygenated blood volume in the brain but using near-infrared light reflections. Galvanic skin response (GSR) has also been used as psychophysiological input for non-muscular control of a computer interface [14].

One brain signal, the mu rhythm, is based on continuous electrical variations in the motor cortex region of the brain according to real and imagined movement. Other signals include slow cortical potentials, P300 potentials, steady state visually-evoked potentials (SSVEPs), and beta rhythms [2]. When properly filtered and translated, these signals are output as machine-readable commands to interface with an application or control a device [2]. For example, these signals can be used to move a cursor on the screen and make selections. Mu-based BCIs can take advantage of the difference in signal properties between idle and active imagery within the motor cortex region of the brain to produce a control signal. The proportional difference in signal properties is measured by a response R-squared value and indicates signal strength or the degree of modulation a person may induce [2, 19, 20].

1.2. Fit

The theoretical concept of fit, used to describe contingent relationships between variables, is classified according to six perspectives [21]: 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 [22] and by pairing certain business strategies with company structure and observing company performance [23].

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 [24] and with fit as moderation [25, 26]. 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” [26, page 1829]. There, the word “match” was used to describe how technology features were moderated by task requirements and individual characteristics to predict performance impacts.

Goodhue and Thompson’s [25] model of the Technology-to-Performance Chain (TPC) initially considered individual characteristics as a component affecting TTF but only tested a subset of the model and did not include this construct. However, Goodhue [26] tested the effect of individual characteristics on TTF but 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.

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 [27] 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.

2. Theoretical Framework

This work describes a framework for ITF as illustrated in Figure 1 which seeks to initially link individual characteristics and features of BCI technologies with human performance using a fit as matching perspective.

![Figure 1. Framework of individual-technology fit](image)

The ITF framework does not include utilization because utilization of BCI technology may be considered mandatory for certain 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” [26, 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.
2.1 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 BCIs. Specifically, ITF is the correspondence between individual characteristics and the BCI technology being used. A strict interpretation of the original TTF 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 wide-ranging control purposes and few users have sufficient experience with these technologies or non-traditional assistive technologies to understand their own fit.

2.2 Technology Characteristics

The technology features of BCIs are based on a taxonomy and attributes of a transducer [28] 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. **Neurological Phenomenon** – Phenomenon used to control the 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).

2.3 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 BCI technologies although there are several assessments of human capabilities ranging from functional limitations to the amount of system training received [29]. Randolph and Moore Jackson [12] proposed a set of characteristics affecting BCI technology control and tested them with fNIR- and GSR-based technologies. Their list ranging from age and athleticism to hair color was based on a review of related literature and discussions with researchers in the fields of BCI and assistive technology concerning observed and hypothetical physiological effects. They found that age, regular consumption of caffeine, and years of education all positively correlated with fNIR control whereas age, sex, hair and skin color, hair texture, meditation, regular consumption of alcohol, and video game experience all positively correlated with GSR control. In a separate study [30], they found that the interaction of age and hand-and-arm movement predicted modulation of the mu rhythm in a mu-based BCI. These studies serve as a good basis for examining individual characteristics as extended and applied to mu-based BCIs.

2.4 Performance

Here, performance is the observable evidence of fit between individual characteristics and a particular BCI technology. As individuals are better matched to BCI interfaces, their performance should increase and vice-versa if ill-matched. In this study, performance is evidenced by the response R-squared value. The response R-squared value is a measure for the degree of modulation of the mu rhythm which may ultimately reflect degree of control by an individual of a mu-based BCI. This measure is widely accepted in the BCI field where mu is generally thought to be a good signal for control [2].

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3. Study

This study investigated ITF of a subset of characteristics previously proposed for investigation with fNIR- and GSR-based interfaces: age (under/over age 25), sex (male/female), instrument playing (yes/no), sports playing (number of sports played), video game experience (high/low), and affective drugs (yes/no). Here, these characteristics were tested with a mu-based BCI.

3.1 Participants

Eighty (80) able-bodied participants (35 male and 45 female) with an average age of 24 (ranging from 17 to 52 years) were screened in total over two separate sessions. Both sessions were conducted on the campus of a large university in the southeastern part of the United States and included students, faculty, and professionals on a voluntary basis. Participants were recruited via word-of-mouth and through university information systems and psychology classes. Participants were compensated for their time by class credit or payment. Individuals participated in only one session each.

3.2 Experimental Procedure

The first screening session took place using version 1.0 of the BCI2000 software for recording and analyzing EEG recordings for control studies [31]. The second session took place using version 2.0 of the same software. Thus, due to differences in software versions, this study considered just one feature of the BCI transducer, feature extraction/translation algorithms, as the distinguishing factor between the BCI technologies being compared. Six features of the transducer were held constant to narrow the scope of this work (endogenous type, EEG biorecording technology, 10-20 system for electrode placement over motor cortex, phenomena in electrical brain activity, continuous output, and idle support in the form of a “rest” state); and one feature was not applicable per the experimental protocol (stimulator).

The screening task was held constant across both sessions. After completing a questionnaire gauging individual characteristics based on the combined work of Randolph and Moore Jackson [12, 30], participants were asked to picture varying hand and foot imagery in conjunction with on-screen prompts but not to physically move these body parts while EEGs were recorded. During the inter-trial intervals, participants were asked not to imagine any movement and remain relaxed and at rest while EEGs were still recorded.

Recordings from 8-64 channels of scalp electrodes were analyzed offline to determine the strength and position of the mu signal measured by a response R-squared value and head mapping. The screening procedure lasted approximately 30 minutes. Participant performance was measured according to the difference between the distribution of mu rhythm amplitudes when the person was attempting a trial versus when he/she was at rest. The response R-squared value was calculated as the proportion of total variance due to the difference between states.

4. Results

Participants’ answers to the pre-session questionnaire were correlated with their response R-squared value for control signal strength resulting from the subsequent screening process. The response R-squared value served as the dependent variable. In addition, the session number (1 or 2) was correlated with the response R-squared value to determine if changes in the technology characteristics also made a difference.

Of the single-factor models that were run, two variables showed significance: session number and video game experience. Session number showed the highest significance of any of the regression models tested ($p = 0.000$, $R^2(adj) = 25.8\%$) and is illustrated in the boxplot in Figure 2. This variable takes into account the technological differences between the two sessions. Because there was a significant difference between the response R-squared values in the two sessions, blocking by session was seen to be effective and kept in subsequent, multi-va riable models.

Figure 2. Boxplot of response R-squared values per session.
Video game experience also showed significance as a single predictor of response R-squared values (p = 0.000, R-Sq(adj) = 17.5%).

The most parsimonious regression equation with the lowest PRESS statistic (prediction error) and standard deviation was the natural log transformation of the response R-squared value versus five variables: session number, instrument playing, affective drugs, sex, and age. Sex of the participant appears to be an important factor because although it is not significant at the 95% level, it is significant at the 90% level, and the standard deviation and PRESS are lower when it is included. Without sex included, the result is S = 0.707014, R-Sq(adj) = 38.5%, and PRESS = 41.9790. Overall, the response R-squared value increased with the first session, playing at least one instrument, not being on affective drugs, being female, and being over the age of 25. The following provides more detail:

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coef</th>
<th>SE Coef</th>
<th>T</th>
<th>P</th>
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<tbody>
<tr>
<td>Constant</td>
<td>-2.6110</td>
<td>0.2461</td>
<td>-10.61</td>
<td>0.000</td>
</tr>
<tr>
<td>Session No_Ses 1</td>
<td>1.1158</td>
<td>0.1807</td>
<td>6.18</td>
<td>0.000</td>
</tr>
<tr>
<td>Instrument - Y/N?_Y</td>
<td>0.5721</td>
<td>0.2021</td>
<td>2.83</td>
<td>0.006</td>
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<tr>
<td>On Drugs?_Yes</td>
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<td>0.1822</td>
<td>-2.61</td>
<td>0.011</td>
</tr>
<tr>
<td>Sex_M</td>
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<td>0.1676</td>
<td>-1.75</td>
<td>0.084</td>
</tr>
<tr>
<td>AGE_1</td>
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<td>0.1804</td>
<td>-3.32</td>
<td>0.001</td>
</tr>
</tbody>
</table>

S = 0.697448  R-Sq = 44.0%  R-Sq(adj) = 40.2%
PRESS = 41.4972  R-Sq(pred) = 35.39%

Analysis of Variance

<table>
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<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>P</th>
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<tbody>
<tr>
<td>Regression</td>
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<td>28.2282</td>
<td>5.6456</td>
<td>11.61</td>
<td>0.000</td>
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<td>Residual Error</td>
<td>74</td>
<td>35.9961</td>
<td>0.4864</td>
<td></td>
<td></td>
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<tr>
<td>Total</td>
<td>79</td>
<td>64.2243</td>
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</table>

6. Conclusions

This study illustrates how individual characteristics may be matched with technology characteristics of a BCI to predict performance using the individual-technology fit model. Here, performance is measured as a person’s ability to control modulation of his/her mu rhythm and thus reflects BCI literacy. It appears that the version of software used in recording and interpreting EEGs matters as there are subtle differences in algorithms and filters used. Further, instrument playing, being on affective drugs, sex, and age also play a key role in predicting mu rhythm modulation. These results are in line with previous studies in the field which have shown counter-intuitive findings that age and control of mu rhythm modulation are inversely related and activities that involve dexterity of the hands such as instrument playing also play a role. In addition, work with patients has shown that medication has direct ties to a person’s alertness levels which affect the ability to concentrate and create clear images. Interestingly, sex is a key factor that has not been previously distinguished for mu-based BCI control, where women performed better than men.

The characteristics considered in this study are just a subset of those presented in other work and cannot represent all of the varied characteristics that a human may possess. Additional factors, such as user interface design and motivation, may also have a significant impact on performance. Despite its limitations, this work provides encouragement for more research to further understand the differences between individuals, technology, and the impacts on BCI design. 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.

7. References


