Appl Psychophysiol Biofeedback
DOI 10.1007/s10484-017-9379-8

Using EEG Frontal Asymmetry to Predict IT User's Perceptions Regarding Usefulness, Ease of Use and Playfulness

Christos N. Moridis[1] · Vasileios Terzis[2] · Anastasios A. Economides[3] · Anna Karlovasitou[4] · Vasileios E. Karabatakis[5]

Abstract Information systems (IS) community is increasingly interested in employing neuroscience tools and methods in order to develop new theories concerning Human–computer interaction (HCI) and further understand IS acceptance models. The new field of NeuroIS has been introduced to address these issues. NeuroIS researchers have proposed encephalography (EEG), among other neuroscience instruments, as a valuable usability metric, when used effectively in appropriately designed experiments. Moreover, numerous researchers have suggested that EEG frontal asymmetry may serve as an important metric of user experience. Based on the aforementioned evidence, this study aims to integrate frontal asymmetry with Technology acceptance model (TAM). Particularly, we assumed that frontal asymmetry might predict users' perceptions regarding Usefulness and Ease of Use. Furthermore, we hypothesized that frontal asymmetry might also affect (influence) users' Perceived Playfulness. Specifically, 82 (43 females and 39 males) undergraduate students were chosen to use a Computer-Based Assessment (while being connected to the EEG) in the context of an introductory informatics course. Results confirmed our hypothesis as well as points of theory about Information technology (IT) acceptance variables. This is one of the first studies to suggest that frontal asymmetry could serve as a valuable tool for examining IT acceptance constructs and better understanding HCI.

Keywords TAM · EEG frontal asymmetry · Perceived playfulness · Perceived usefulness · Perceived ease of use

✉ Christos N. Moridis
cmoridis@netvalue.gr

1 School of Science and Technology, International Hellenic University, 14th km Thessaloniki – Moudania, Thessaloniki, Greece

2 Hellenic Electricity Distribution, Network Operator S.A., 20, Perraivou & 5, Kallirois str., Athens, Greece

3 Interdepartmental Programme of Postgraduate Studies in Information Systems, University of Macedonia, Egnatia Street 156, 540 06 Thessaloniki, Greece

4 Laboratory of Clinical Neurophysiology AHEPA Hospital, Aristotle University of Thessaloniki, University Campus, 54124 Thessaloniki, Greece

5 Laboratory of Experimental Ophthalmology, School of Medicine, Aristotle University of Thessaloniki, University Campus, 54124 Thessaloniki, Greece

Introduction

Information systems (IS) community is more and more acknowledging the need to effectively employ methods and practices of neuroscience in order to better comprehend issues that have to do with the way people interact with IS or to develop new theories about human behaviours that have to do with information technologies (Riedl et al. 2010a). Thus, in recent years, a new field has been introduced, called NeuroIS (Dimoka et al. 2007). Clearly, this involves a joint effort of IS researchers, neuroscientists, and scientists of other related disciplines (e.g. psychology). Accordingly, methodologies and tools from various fields need to be integrated, adapted and employed appropriately to develop a sound ground of NeuroIS research practices.

Traditionally, IS researchers collect data using surveys and other self-report methods. The first model was the theory of reasoned action (TRA) (Fishbein and Ajzen 1975). TRA was ancestor of the IT acceptance models. Attitudes and subjective norms are the two major constructs in TRA. Based on TRA, the technology acceptance model (TAM) was developed to predict IT acceptance by

Published online: 04 September 2017

using Perceived Usefulness (PU) and Perceived Ease of Use (PEOU; Davis 1989). TAM is the most popular model and it has been used in numerous studies regarding technology acceptance.

Venkatesh et al. (2003) proposed a unified model, called the unified theory of acceptance and use of technology (UTAUT). UTUAT explains that the core determinants of IT acceptance are four variables and the other four variables are moderators of the main relationships. UTUAT states that Performance Expectancy which is an extension of Usefulness from TAM, Effort Expectancy which is an extension of Ease of Use from TAM, Social Influence and Facilitating Conditions are determinants of Behavioural Intention or Use Behaviour, and that Gender, Age, Experience and Voluntariness of use have moderating effects on the acceptance of IT.

PU and PEOU are considered as the two most important determinants of any IT acceptance model. In addition, many studies proposed and used Perceived Playfulness as a crucial factor of User's acceptance (Moon and Kim 2001).

While these methods have definitely advanced the IS field, self-reported data are prone to common method bias (Dimoka et al. 2007). In relation to this, Dimoka et al. (2007, p. 2) suggested in one of the first publications on this concern: "By directly asking the brain, not the person, neuroimaging techniques allow an objective, reliable and unbiased measurement of thoughts, beliefs, and feelings and link them to specific human processes (e.g., decisions, choices, and behavior)". Nevertheless, the plain use of neuroscientific measurement techniques will undoubtedly not be enough (Vom Brocke et al. 2011).

Cognitive neuroscience makes use of a diversity of tools such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), positron emission tomography, and skin conductance response. Appropriate use of these tools, in the context of properly designed experiments, can yield very useful brain and psychophysiological data to accelerate the understanding of human behaviour across so many different fields, such as IT usage, economics, psychology, and marketing (Glimcher et al. 2009). Even though relating and synchronizing two or even more tools throughout such experiments could significantly increase the quality of data, many researchers have employed only EEG methods in their experiments. The key benefits of EEG are that it is a reasonably low-cost, fast, and safe way to study functioning of different parts of the brain (Davidson 1988).

Hence, EEG can be a valuable usability metric in the context of NeuroIS research. Particularly, there is a robust body of literature demonstrating that relatively greater left frontal activity is associated with anger, approach-related motivation, and positive affect, and that relatively greater right frontal activity is associated with negative affect and withdrawal-related motivation (Harmon-Jones 2003; Coan and Allen 2004).

Importantly, research has established that the EEG alpha band (8–12 Hz) is inversely associated to underlying cortical activity, as reductions in alpha are expected to be measured when the underlying cortical structures move to active processing (Coan and Allen 2004). Accordingly, in the EEG literature left frontal versus right frontal activation is showed by lower EEG power values in the alpha frequency band. Davidson et al. (1979) provided one of the first reports that related left-frontal decrease in the quantity of the alpha bandwidth with positive affect. Quite the opposite, negative affect was associated to a reversal of the frontal alpha ratio score.

However, EEG measurements may be biased from a wide variety of sources, such as body movement, time of day, room temperature etc. Moreover, sensors might frequently fail and produce poor or missing data resulting in a significant reduction in the performance of the pattern recognition system (Kapoor and Picard 2005). Nevertheless, the expanding literature on procedural issues in the evaluation of EEG asymmetry is leading to essential improvements that will advance the reliability and validity of these measures.

Frontal EEG asymmetry has been shown to predict current affect without bias from situational or identity-related values (Steiner and Coan 2011). On the other hand, self-reported measures have been shown to be influenced both by affective feeling taking place during the real-time experience and situational or identity-related values about what one's perceptions ought to be (Steiner and Coan 2011). For instance, an assiduous student may be biased to report positively about a testing system. Therefore, taking EEG measurements during student's interaction with the system and integrating EEG frontal asymmetry with the IS acceptance model may provide a more veridical aspect of student's experience.

Preliminary results from a previous study (Moridis et al. 2012) indicated that frontal asymmetry explains student's perceptions regarding usefulness and ease of use. Based on that study, which is essential towards understanding the practical use of EEG frontal asymmetry as a potential neurophysiological tool to measure user's perceptions, in this study we go even further. We confirm findings of the previous study concerning PEOU and PU variables, but we also provide evidence that frontal asymmetry can be valuable in explaining student's perceptions regarding playfulness. Thus, this study is a more complete attempt to integrate EEG frontal asymmetry with TAM in order to associate brain activation with the three most important variables of TAM: PU, PEOU, and Perceived Playfulness.

Specifically, this study examines how alpha frontal asymmetry at medial (F3–F4) and lateral frontal (F7–F8) scalp locations can explain the most important variables of IT acceptance, since especially those asymmetry scores have been shown to be related to emotion-connected and approach-oriented/withdrawal-oriented behaviours (Coan and Allen 2003; Davidson and Fox 1989; Davidson et al. 1990; Dawson et al. 1992; Harmon-Jones et al. 2011; Fox 1994; Fox et al. 2001). Asymmetry calculated at other frontal locations may also provide useful explanation of IT acceptance variables.

Particularly, this paper focuses on changes at F3–F4 and F7–F8 asymmetry scores during the use of a computer-based assessment (CBA) and whether these changes could explain user perceptions regarding Playfulness, Usefulness, Ease of Use and potentially behavioral intention to use the CBA. Therefore, this study contributes to the NeuroIS field by using EEG frontal asymmetry scores in order to explain the most notable model regarding IT acceptance, the TAM (Davis 1989). We consider this to be a first step towards effectively employing EEG frontal asymmetry to define IS acceptance variables.

The organization of this paper is the following: In section 2, related studies in NeuroIS are briefly presented. Section 3 presents the proposed model. Section 4 describes the experimental method. Section 5 demonstrates the data analysis (EEG and research questionnaire data) and section 6 presents the results. Finally, section 7 discusses the research findings and presents implications, limitations, and conclusions of this study, as well as directions for further research.

Related Research

The integration of IS research with neuroscience (NeuroIS) raises questions and opportunities for the future. In this new field, researchers try to address fundamental concerns and to develop new trends. Firstly, they attempt to give a definition of NeuroIS. Moreover, they investigate which neuroscience tools or methods might be beneficial for IS field and how neuroscience might advance IS research (Riedl et al. 2010a).

Dimoka et al. (2010) presented seven directives that will help IS researchers regarding the proper use of neuroscience in IS: (1) examine the relationship of IS variables with specific neural mechanisms; (2) integrate IS data with neuroscientific data; (3) measure new processes that could be examined through neuroscience measurements; (4) investigate brain activation produced by IT stimuli to predict antecedents of IS variables; (5) measure brain activation to forecast perceptions and behavior regarding IS variables; (6) examine the timing of brain activations in order to determine causality among IS variables; (7) further expand existing IS theories through brain's functionality.

Moreover, Liapis and Chatterjee (2011) developed the NeuroIS design science model (NDSM). NDSM is a framework that will help IS researchers further understand human and interface interaction.

NeuroIS studies used mainly FMRI and EEG to perform their experiments. Firstly, brain–computer interfaces were used to examine new aspects and opportunities regarding locked-in patients (people who are totally paralyzed and not capable of speaking, but cognitively unharmed) (Moore et al. 2005; Randolph et al. 2006). Moreover, researchers examined internet users' stress during their activities with physiological measurements (Galletta et al. 2007). Furthermore, another aspect that troubles IS researchers is the Trust variable. NeuroIS studies used FMRI to collect data and to associate them with Trust. Riedl et al. (2010b) performed a research in the context of e-commerce and they investigated gender differences regarding trustworthiness through brain activity.

Another study in the context of e-commerce examined users' Trust and Distrust by associating these opposite IS variables with activation of different brain areas (Dimoka 2010). Dimoka (2010) provided evidence that Trust is related to the brain's reward, prediction, and uncertainty areas, whereas Distrust is associated with the brain's intense emotions and fear of loss regions. More importantly, the study indicated that credibility and discredibility are frequently associated with the brain's cognitive areas (prefrontal cortex), while benevolence and malevolence are commonly associated with the emotional areas (limbic system).

Except of FMRI, EEG was also used to provide evidences regarding brain-computer interfaces. Specifically, Lee and Tan (2006) investigated and determined computer user's engagement on a particular mental task at an exact point of time (Lee and Tan 2006). Interestingly, they provided evidence that EEG has potential as a broad physiological input sensor for distinguishing between tasks in a wide variety of computing applications without demanding detailed prior knowledge of the tasks. They achieved a mean classification precision of 84.0% in individuals performing one of three cognitive tasks and a mean classification accuracy of 92.4% in subjects performing three tasks that involved non-cognitive features.

Furthermore, an important aspect of IS researchers is the development of new theories or models regarding IS acceptance. These studies are based on the TAM (Davis 1989). Dimoka and Davis (2008) examined the relationship of the two most important variables (PU, PEOU) of TAM with specific neural and brain areas by using a FMRI. Their findings (Dimoka and Davis 2008), are in line with relevant cognitive neuroscience literature, indicating that high levels of PU stimulate the caudate nucleus and the anterior cingulate cortex, while low levels of PU stimulate the insular cortex. The caudate nucleus and anterior cingulate cortex are activated because of anticipated rewards, while stimulation in the insular cortex is related to intense emotions due to fears of loss. Furthermore, according to this study, PEOU seems to activate the DLPFC, an area associated with the sequential execution of actions during controlled processing. Moreover, higher levels of PEOU were correlated with the level of brain stimulation in the DLPFC. Lastly, high intentions to use were found to stimulate the VLPFC and the bilateral amygdale, whereas low intentions to use were shown to stimulate left putamen. According to the cognitive neuroscience literature, the VLPFC relates to intentions to participate in a behavior, while bilateral amygdale activation relates to expectation of a positive reward. Left putamen activation relates to recognizing an error in reward prediction.

Based on previous studies and guidelines regarding the implementation of a NeuroIS research, this study investigates how EEG measurements and especially frontal asymmetry could be integrated with traditional measurements in order to predict user's perceptions regarding Usefulness, Playfulness and Ease of Use.

Proposed Model

Perceived Playfulness

Davis et al. (1992) embedded intrinsic motivation in their research regarding TAM. Specifically, they suggested that computer user's intrinsic enjoyment might influence behavioral intention.

Moon and Kim (2001) determined Playfulness as the pleasure the individual feels objectively when committing a particular behavior or carrying out a particular activity. Moon and Kim (2001) revealed Playfulness as a key factor for user's acceptance of the Internet. Playfulness includes enjoyment, curiosity and concentration; consequently it is a variable more comprehensive than pleasure (Moon and Kim 2001). Previous studies supported that Perceived Playfulness is a crucial predictor of users' behavioral intention to use a CBA (Terzis et al. 2012). Therefore, we hypothesized (Fig. 1):

H1 Perceived Playfulness will have a positive effect on the Behavioural Intention to use CBA.

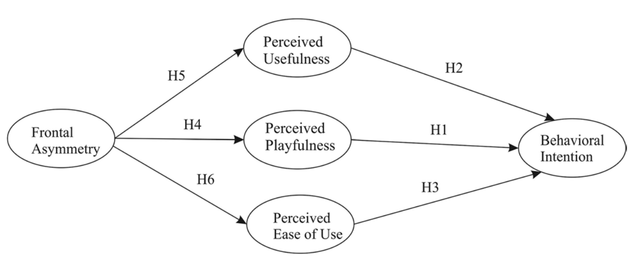

Fig. 1 The research model

Perceived Usefulness

PU is one of the most important predictors of technology acceptance (Davis 1989). PU can be described as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis 1989, p. 2). Previous studies highlighted that PU has significant positive effect on the Behavioral Intention to use an e-learning system or a CBA (e.g. Lee 2008; Ong and Lai 2006; Terzis and Economides 2011). In this study, PU is defined as the degree to which an individual perceives that the use of the particular CBA enhances his or her efficiency in learning. Thus, we believe that PU will be a strong predictor of Behavioral Intention to Use the CBA. Therefore, we hypothesized (Fig. 1):

H2 Perceived Usefulness will have a positive effect on the Behavioural Intention to use CBA.

Perceived Ease of Use

PEOU is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis 1989, p. 2). IS researchers have revealed that PEOU has an important direct effect on Behavioral Intention to Use an e-learning system or a CBA (Agarwal and Prasad 1999; Terzis and Economides 2011; Venkatesh 1999; Venkatesh and Davis 1996). Thus, we hypothesized (Fig. 1):

H3 Perceived Ease of Use will have a positive effect on the Behavioural Intention to use CBA.

Frontal Asymmetry

Earlier in the introduction we explained that left frontal versus right frontal activation is specified by lower EEG power values in the alpha frequency band. There is research evidence showing that the difference of alpha frequency in frontal cortex is related to individual's positive versus negative perceptions and approach/withdraw motivation concerning the stimuli (Davidson et al. 1979).

The aforesaid occurrences could be stimulated (among other causes) throughout CBA by the system's ease of use, usefulness and playfulness. Accordingly, for example, we would assume that students who had a greater approach motivation (as shown by greater left frontal activation), during their interaction with the system, would also report a greater sense of playfulness, usefulness and ease of use. Therefore, we expected that greater left versus right frontal activation would be positively associated with users' perceptions regarding usefulness, ease of use, and playfulness, while answering the questionnaire after the end of the CBA. Therefore, we hypothesized that (Fig. 1):

H4 Frontal Asymmetry will be positively associated with Perceived Playfulness.

H5 Frontal Asymmetry will be positively associated with Perceived Usefulness.

H6 Frontal Asymmetry will be positively associated with Perceived Ease of Use.

Method

Participants

First year undergraduate students enrolled in an introductory informatics course were chosen to participate in this study. Students were informed that they could optionally take part in a CBA to help them evaluate their knowledge before the final exam. Students, who chosen this option, were then asked to volunteer to use the CBA while connected to EEG in order to serve as subjects of a research study (subjects were not informed about the intention of the study). Those who volunteered completed a short survey and signed an informed consent. Only volunteer students who were right handed, in good mental health (don't take medication that affects the central nervous system) and had normal or corrected to normal vision were chosen. The sample was limited to right-handed participants because hemispheric specialization has been identified to be different in left-handed subjects (Willems et al. 2014). Thus, 87 subjects in total were selected to participate in the current stage. However, five of them changed their mind about being connected to the EEG while taking the CBA, which resulted in 82 participants (43 females and 39 males). Participants were instructed to sleep sufficiently and not to consume any alcohol related product the night before the experimental procedure.

Procedure

Each participant was tested individually. Electrodes were appropriately placed on subject's scalp and the EEG was adjusted accordingly (see "EEG Recording, Reduction and Analysis" section). At least 6 min of eyes open-eyes closed EEG data were collected from the 19 monopolar electrodes sites. The purpose of this recording was to have the chance to correct any technical problems before the real recordings when the students were using the CBA. After that, the participant used the CBA. The CBA test consisted of 20 multiple choice questions and students had to complete the test in 20 min. When participants finished the test, they were disconnected from the EEG and were given a few minutes to relax. Participants then completed a questionnaire (Table 1), in order to examine the four latent variables of the model. For the four latent variables, we adopted three items for Perceived Playfulness from Moon and Kim (2001), three items regarding PU, three items for PEOU, and three items for Behavioral Intention to use from Davis (1989), modified to be relevant in CBA context (Terzis and Economides 2011). All items were measured on a seven point Likert-type scale with 1 = strongly disagree to 7 = strongly agree.

Data Analysis

EEG Recording, Reduction and Analysis

The recordings took place in a calm room, while at least 6 min of eyes open-eyes closed EEG data were collected from the 19 monopolar electrodes sites (Fpl, Fp2, F3, F4, F7, F8, Fz, C3, C4, Cz, T3, T4, T5, T6, P3, P4, Pz, O1 and O2 sites) (Fig. 2). The purpose of this recording was to have the chance to correct any technical problems before the real recordings when the students were using the CBA.

Table 1 Specific questionnaire items used

Constructs	Items	
Perceived usefulness	PU1	Using the Computer Based Assessment (CBA) will improve my work
	PU2	Using the Computer Based Assessment (CBA) will enhance my effectiveness
	PU3	Using the Computer Based Assessment (CBA) will increase my productivity
Perceived ease of use	PEOU1	My interaction with the system is clear and understandable
	PEOU2	It is easy for me to become skilful at using the system
	PEOU3	I find the system easy to use
Perceived playfulness	PP1	Using CBA keeps me happy for my task
	PP2	Using CBA gives me enjoyment for my learning
	PP3	Using CBA, my curiosity stimulates
Behavioral intention to use the CBA	BI1	I intend to use CBA in the future
	BI2	I predict I would use CBA in the future
	BI3	I plan to use CBA in the future

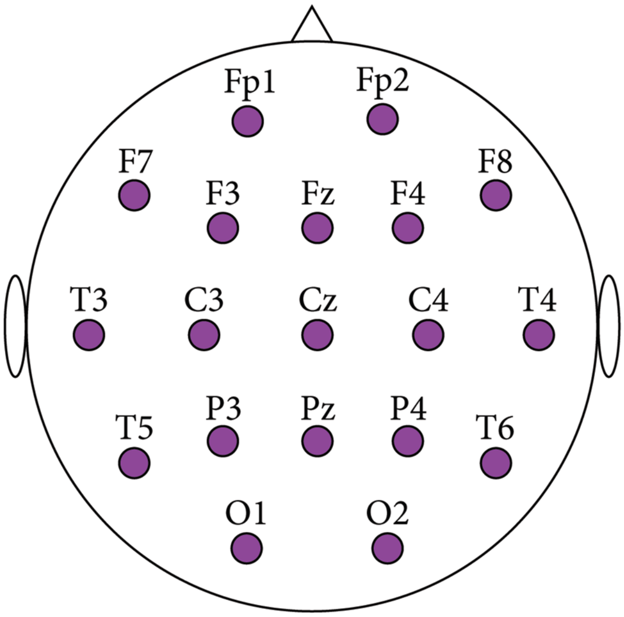

Fig. 2 Scalp EEG electrodes

The international 10/20 System (average reference montage) for electrode placement was used with a Neuron-Spectrum-4 (Neurosoft-Medical Diagnostic Equipment, Russia). In an average reference montage the reference signal is calculated by using the average of all electrodes (Dien 1998). All electrode impedances were <5 kΩ, while the sampling rate for all measurements was 500 Hz.

EEG records were visually examined by three independent experts. Movement and muscle artifacts were marked and excluded from further analysis. Then, independent component analysis (ICA) from EEGLAB was applied to identify and remove more sources of artifacts (Delorme and Makeig 2004). The ICA was used to detect and eliminate the following types of non-brain artifacts from EEG data: eye movements and eye blinks, muscle activity and line noise. After that, the EEG records were examined again by three independent experts in order to confirm whether artifacts had been successfully removed.

Thus, at least 8 min of artifact-free data were extracted from each participant's EEG total record for quantitative analysis. A typical power spectral density estimator was applied (based on the squared absolute value of the Fourier transform) with Hamming windowing. Average alpha (8–12 Hz) power (microvolts squared) was after that natural log transformed in order to normalize the distributions of power values, as these distributions tend to be positively skewed. This practice has been widely used and follows the recommendations of Davidson et al. (1990). Finally, frontal EEG asymmetry scores associated with medial (F3–F4) and lateral frontal (F7–F8) scalp locations, were calculated for alpha band following the methodology described by Davidson (1988):

$$\frac{Right - Left}{Right + Left} \tag{1}$$

The difference in score hence gives a simple scale (1) accounting for the relative activity of the right and left hemispheres, with higher scores indicating relatively greater left frontal activity (alpha is inversely related to activity) (Allen et al. 2004). Thus, a value of 0.5 would represent a strong 50% right side asymmetry and therefore considerable left side activation.

Partial Least Squares Analysis

This research used partial least-squares (PLS) analysis to measure the structural and the measurement model. PLS is more appropriate for our research than covariance-based structural equation modelling (CBSEM) for the following reasons: (1) this research used a relative small sample, (2) the aim of this research is to develop a new theory and not to test a theory (Fornell and Bookstein 1982), (3) this study examined if EEG frontal asymmetry could predict important determinants of intention to use. (4) PLS is better suited for prediction. (Urbach and Ahlemann 2010; Chin 1998; Falk and Miller 1992).

Previous studies recommended regarding sample size a value equal or larger than the most complex variable or the largest number of predictors. Specifically a sample must be ten times larger than the number of items of the most complex construct; or ten times larger than the largest number of independent variables impact a dependent variable (Chin 1998). In our study, all constructs had three items and the largest number of predictors was 3. Thus, the 82 participants in our study are considered as an adequate sample. SmartPLS 2.0 was used to perform data analysis for the measurement and structural model (Ringle et al. 2005).

Measurement model's reliability and validity was tested through unidimensionality, indicator validity, internal consistency, convergent validity and discriminant validity. Unidimensionality and indicator validity is tested by measuring items' factor loading. A value higher than 0.7 on the corresponded construct is considered as significant. Internal consistency was measured with two criteria: (1) Cronbach's alpha and (2) composite reliability. Values higher than 0.7 for both criteria are reliable (Agarwal and Karahanna 2000; Compeau et al. 1999). Convergent validity was tested through average variance extracted (AVE) of each variable. A value of at least 0.5 is significant. Discriminant validity is measured with AVE's squared root of each construct. This value should be higher than any correlation with every other construct (Barclay et al. 1995; Chin 1998; Fornell and Larcker 1981).

The assessment of structural model is conducted by two methods. Firstly, we examine the variance measured (R2). Chin (1998) proposed values of approximately 0.670 substantial, values around 0.333 average, and values of 0.190 lower weak. Secondly, we measured the significance of the path coefficients through the bootstrapping procedure and *t*-values calculation.

Results

Tables 2 and 3 demonstrate the results regarding the measurement model's validity and reliability tests. Table 2 displays factor loadings, composite reliability, Cronbach's alpha and AVE of each construct. All criteria were larger than the minimum recommended values described in "Data Analysis" section. Therefore, unidimensionality, indicator validity, internal consistency, and convergent validity are confirmed. Moreover, Table 3 verified the discriminant validity. The bold diagonal elements are the square root of each construct's AVE, while the other values are the constructs' correlations among them. All the AVEs are larger than any other correlation, consequently discriminant validity is confirmed. Therefore, data confirmed measurement model's reliability and validity.

Table 4 and Fig. 3 display the results for the structural model. Regarding TAM's variables, we find that Perceived Playfulness and PEOU are strong predictors of Behavioral Intention to Use a computer based assessment system. On the other hand, the effect of PU on Behavioral Intention was not supported. Moreover, the results showed that frontal asymmetry could be a strong determinant of PU, Perceived Playfulness and PEOU. Furthermore, EEG frontal asymmetry is a strong indirect predictor of Behavioral Intention to Use the CBA. The indirect effect of EEG frontal asymmetry

Table 2 Results for the measurement model

Construct Items	Mean	Standard deviation	Factor loading	Cronbach a	Composite reliability	AVE
Behavioral intention to use	5.76	1.03		0.93	0.95	0.88
BI1			0.94			
BI2			0.95			
BI3			0.92			
Perceived playfulness	5.73	0.90		0.90	0.93	0.82
PP1			0.90			
PP2			0.92			
PP3			0.90			
Perceived usefulness	5.61	1.01		0.91	0.94	0.85
PU1			0.90			
PU2			0.93			
PU3			0.92			
Perceived ease of use	5.66	0.99		0.92	0.94	0.86
PEOU1			0.91			
PEOU2			0.93			
PEOU3			0.93			
Medial-frontal asymmetry F3–F4	−0.03	2.07		1	1	1
Lateral-frontal asymmetry F7–F8	0.24	5.40		1	1	1

Table 3 Discriminant validity for the measurement model

Construct	Behavioral intention to use	Perceived playfulness	Perceived usefulness	Perceived ease of use	Medial/lateral frontal asymmetry
Behavioral intention to use	0.94				
Perceived playfulness	0.85	0.91			
Perceived usefulness	0.83	0.76	0.92		
Perceived ease of use	0.88	0.82	0.83	0.93	
Medial/lateral frontal asymmetry	0.37	0.43	0.36	0.43	1

Table 4 Hypothesis testing results, significant values in bold (*p < 0.01)

Hypothesis	Path	Path coefficient		t value		Results
		F3–F4	F7–F8	F3–F4	F7–F8	
H1	PP→BI	**0.34***	**0.34***	**3.84**	**3.62**	Support
H2	PU→BI	0.22	0.22	1.22	1.21	Not support
H3	PEOU→BI	**0.41***	**0.41***	**3.17**	**3.53**	Support
H4	FA→PP	**0.44***	**0.48***	**5.45**	**9.27**	Support
H5	FA→PU	**0.36***	**0.39***	**3.73**	**4.12**	Support
H6	FA→PEOU	**0.43***	**0.43***	**5.49**	**6.57**	Support

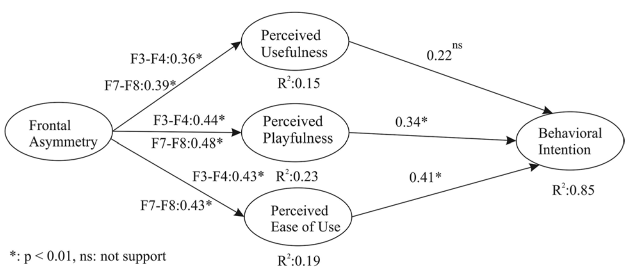

Fig. 3 Path coefficients of the research model

on Behavioral Intention is 0.41. Finally, the model explains almost the 85% of variance in Behavioral Intention to Use.

The measurement and the structural model have almost the same results for medial (F3–F4) and lateral (F7–F8) frontal asymmetries. The mean and standard deviation for lateral (F7–F8) frontal asymmetries were higher than medial (F3–F4) frontal asymmetries. However, the criteria for the validity and the reliability of the measurement model remained the same for medial and lateral frontal asymmetries. Regarding the structural model, F7–F8 lateral frontal asymmetry path coefficients were slightly higher than F3–F4 medial frontal asymmetry path coefficients on PU and Perceived Playfulness (Table 4; Fig. 3).

Discussion and Conclusions

Neuroscience techniques and methods reveal opportunities for measuring important variables that are hard or even impossible to evaluate using traditional approaches (Loos et al. 2010). While IS researchers are employing cognitive neuroscience in order to advance beyond the already well-known variables of technology adoption, this study focuses on the established constructs of Perceived Playfulness, PU, and PEOU. Since our intention here is to highlight the potential importance of EEG frontal asymmetry as an effective method to predict IT user's perceptions, we used familiar constructs to help form a starting point towards this direction.

The findings of this study suggest that frontal asymmetry predicts student's perceptions regarding playfulness, usefulness and ease of use. In general, results showed that the more students' left frontal cortex was activated while interacting with the CBA, the more they reported their experience with the system as playful, useful and easy to use. Thus, this paper provides evidence that activity in the areas of frontal lobes of the brain determines the three most important variables of IS acceptance. In that sense, the findings of this study clearly imply that frontal cortex may hold a vital role in NeuroIS research and as such it should be further examined in the future.

However, it is important to call attention to the fact that the frontal asymmetries observed in this study are components of a larger circuit and that other parts of the circuitry are essential to fully comprehend and explain users' experience. Thus, other components of brain circuitry are certainly important for analysing many of the psychological phenomena related to the IT variables involved in this study. Nevertheless, since the EEG measure (frontal asymmetry), employed here, do not directly reflect activity in other components of the circuitry, these other neural circuits have been disregarded. In the future, we plan to evolve our research in order to take into account other parts of the brain as well.

Moreover, research has suggested that the valence of an emotion may be distinguishable from the motivational direction of that emotion, so that emotions of negative valence, such as anger, can be approach motivating (Harmon-Jones et al. 2010). In this regard, research evidence has associated left-lateralized prefrontal activity with higher levels of reported anger (Harmon-Jones 2003). What is important here is that asymmetric frontal cortical activity is certainly tracking approach motivation, regardless of the emotional valence of that motivation (Harmon-Jones et al. 2010). This, however, can have serious implications when using frontal asymmetry to define IS acceptance variables.

Could it be that approach motivation of negatively valenced emotions was the reason for greater left versus right frontal asymmetry in this study? Negative emotions (e.g. anger) not often evoke approach motivation. The relevant literature, as discussed earlier, has mostly associated greater left versus right frontal asymmetry with greater positive versus negative affect. Most importantly, students answering the questionnaire after the end of the CBA strengthens the validity of research results. In that sense, the research methodology followed in this study is in inline with the NeuroIS community practices to combine neuroscience tools and methods with self-report measures in order to cross-validate findings from neuroscience and traditional methods and thus increase the validity and reliability of research findings.

The data revealed several interesting findings which may be useful to: (1) the development of new theories; (2) the developers regarding the designing, acceptance and adoption of new software and hardware systems; (3) educators and business practitioners by providing new aspects regarding their IS systems or products.

However, this study has some limitations. As one of the first attempts for the development of an acceptance model using physiological data, the results of this study should be treated as indicative and not as conclusive. Future studies should further investigate the association of frontal asymmetry with other important IS acceptance variables. Secondly, this research used a very specific sample of students to respond regarding their beliefs. The proposed model has to be applied in other groups with other characteristics (e.g. age, occupation) or organizations (e.g. companies) for further confirmation. Thirdly, even if we have employed PLS analysis which is appropriate for small samples, this study might have benefit from a larger sample.

Perhaps the most debatable limitation of this study concerns the circumstances of the experiment. Obviously, the situation is artificial, because in real life students sit in front of their computers in a more comfortable and calm environment, without electrodes placed on their scalp. Nevertheless, it has not yet been defined whether this limitation weakens or enhances the actual results.

Another important issue is that in NeuroIS experiments, neurophysiological data are recorded real time during users' interaction with the system. Nevertheless, users answer a questionnaire after their interaction with the system has ended. Moreover, subjective and physiological measures do not always agree, which indicates that physiological data may detect responses that users are either unconscious of or cannot recall at post-session subjective assessment (Wilson and Sasse 2004). In this paper, we would have expected greater rightward frontal asymmetry with such favorable behavioral responses to the CBA. Interestingly, the aforementioned factors could provide some explanation for that inconsistency.

In the future, we intend to follow a gender specific approach in order to gather data that could provide useful explanation of males and females differentiation regarding frontal asymmetry and their perceptions while interacting with an IS system. Moreover, this approach could help confirm or further expand points of theory about gender differences concerning IS acceptance variables. Furthermore, we also plan to extend this study by taking into consideration results from other frontal asymmetry scalp locations (e.g. FP1–FP2).

To our best knowledge this is still the first research paper integrating EEG frontal asymmetry to TAM. Other NeuroIS researchers have used subjective as well as EEG data to investigate the role of emotions and aesthetics in ICT usage (Bhandari and Chang 2014), to evaluate brain-computer interfaces (Milic 2017), to examine cognitive and emotional reactions to software structure (Minas et al. 2017), and even to better understand activities performed on mobile devices (Hollingsworth and Randolph 2015).

Brain-waves based procedures would significantly enrich information systems acceptance research portfolio and help developers evaluate their systems. The integration of EEG-based research with EMG, GSR, FMRI and traditional self-report methods would provide innovative explanations in the context of IS acceptance.

To conclude this research study is essential towards further understanding the practical use of neuroscience research in information systems. In particular, this study presents EEG frontal asymmetry as a potential neurophysiological tool to measure user's perceptions regarding system's playfulness, usefulness and ease of use.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed Consent Informed consent was obtained from all individual participants included in the study.

References

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly, 24*, 665–694.

Agarwal, R., & Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies? *Decision Sciences, 30*(2), 361–391.

Allen, J. J. B., Coan, J. A., & Nazarian, M. (2004). Issues and assumptions on the road from raw signals to metrics of frontal asymmetry in emotion. *Biological Psychology, 67*, 183–218.

Barclay, D., Higgins, C., & Thompson, R. (1995). The Partial Least Squares approach to causal modelling: Personal computer adoption and use as an illustration. *Technology Studies, 2*(1), 285–309.

Bhandari, U., & Chang, K. (2014). Role of emotions and aesthetics in ICT usage for underserved communities: a NeuroIS investigation. In *Proceedings of ICIS 2014*. Auckland: AIS

Chin, W. W. (1998). The partial least squares approach to structural equation Modeling. In G. A. Marcoulides (Ed.), *Modern business research methods* (pp. 295–336). Mahwah, NJ: Lawrence Erlbaum Associates.

Coan, J. A., & Allen, J.J.B. (2003). Frontal EEG asymmetry and the behavioral activation and inhibition systems. *Psychophysiology, 40*, 106–114.

Coan, J. A., & Allen, J. J. B. (2004). Frontal EEG asymmetry as a moderator and mediator of emotion. *Biological Psychology, 67*, 7–49.

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly, 23*, 145–158.

Davidson, R. J. (1988). EEG measures of cerebral asymmetry: Conceptual and methodological issues. *International Journal of Neuroscience, 39*, 71–89.

Davidson, R. J., Ekman, P., Saron, C., Senulis, J., & Friesen, W. V. (1990). Approach/withdrawal and cerebral asymmetry: Emotional expression and brain physiology. I. *Journal of Personality and Social Psychology, 58*, 330–341.

Davidson, R. J., & Fox, N. A. (1989). Frontal brain asymmetry predicts infants' response to maternal separation. *Journal of Abnormal Psychology, 98*, 127–131.

Davidson, R. J., Taylor, N., & Saron, C. (1979). Hemisphericity and styles of information processing: Individual differences in EEG asymmetry and their relationship to cognitive performance. In *Abstracts of the papers presented at the eighteenth annual meeting of the society for psychophysiological research. Psychophysiology. 16*, 197.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*, 319–340.

Davis, F. D., Bagozzi, R. P., Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology, 22*(14), 1111–1132.

Dawson, G., Panagiotides, H., Klinger, L. G., & Hill, D. (1992). The role of frontal lobe functioning in the development of infant self-regulatory behavior. *Brain and Cognition, 20*, 162–176.

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods, 134*, 9–21.

Dien, J. (1998). Issues in the application of the average reference: Review, critiques, and recommendations. *Behavior Research Methods, Instruments, & Computers, 30*, 34–43.

Dimoka, A. (2010). What does the brain tell us about trust and distrust? evidence from a functional neuroimaging study. *MIS Quarterly, 34*(2), 373–396.

Dimoka, A., & Davis, F. D. (2008). Where does tam reside in the brain? the neural mechanisms underlying technology adoption. In *ICIS 2008 Proceedings*. Paper 169

Dimoka, A., Pavlou, P. A., & Davis, F. D. (2007). NEUROIS: The potential of cognitive neuroscience for information systems research. In *Proceedings of the 28th international conference on information systems (ICIS)* (pp 1–20).

Dimoka, A., Pavlou, P. A., & Davis, F. D. (2010). NEURO-IS: The potential of cognitive neuroscience for information systems research. In *Information systems research. Articles in advance* (pp. 1–18).

Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. Akron, OH: University of Akron Press.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behayior: An introduction to theory and research*. Reading, MA: Addison-Wesley.

Fornell, C., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research, 19*, 440–452.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equations models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

Fox, N. A. (1994). Dynamic cerebral processes underlying emotion regulation. In, The development of emotion regulation: Biological and behavioral considerations. *Monographs of the Society for Research in Child Development, 59*(2–3), 240.

Fox, N. A., Henderson, H. A., Rubin, K. H., Calkins, S. D., & Schmidt, L. A. (2001). Continuity and discontinuity of behavioral inhibition and exuberance: Psychophysiological and behavioral influences across the first four years of life. *Child Development, 72*, 1–21.

Galletta, D., et al. (2007). Does our web site stress you out? In *Proceedings of the international conference on information systems*. Paper 50 (research in progress).

Glimcher, P. W., et al. (Eds.). (2009). *Neuroeconomics: Decision making and the brain*. Amsterdam: Academic Press.

Harmon-Jones, E. (2003). Clarifying the emotive functions of asymmetrical frontal cortical activity. *Psychophysiology, 40*, 838–848.

Harmon-Jones, E., Gable, P. A., & Peterson, C. K. (2010). The role of asymmetric frontal cortical activity in emotion-related phenomena: A review and update. *Biological Psychology, 84*, 451–462.

Harmon-Jones, E., Harmon-Jones, C., Serra, R., & Gable, P. A. (2011). The effect of commitment on relative left frontal cortical activity: Tests of the action-based model of dissonance. *Personality & Social Psychology Bulletin, 37*(3), 395–408.

Hollingsworth, C. L., Randolph, A. B. (2015) Using NeuroIS to better understand activities performed on mobile devices. In: F. Davis, R. Riedl, vom Brocke J., P. M. Léger & A. Randolph (Eds.), *Information systems and neuroscience. Lecture notes in information systems and organisation* (Vol. 10). Cham: Springer.

Kapoor, A., & Picard, R. W. (2005). Multimodal affect recognition in learning environments. In *Proceedings of the 13th annual ACM international conference on multimedia* (pp. 677–682). Singapore: Hilton

Lee, J. C., & Tan, D. S. (2006). Using a low-cost electroencephalograph for task classification in HCI research. In *Proceedings of the 19th annual ACM symposium on user interface software and technology in Montreux, Switzerland*, October 15–18 (pp. 81–90). New York: ACM Press.

Lee, Y. C. (2008). The role of perceived resources in online learning adoption. *Computers & Education, 50*(4), 1423–1438.

Liapis, C., & Chatterjee, S. (2011). On a NeuroIS design science model. *Lecture Notes in Computer Science. 6629*, 440–451.

Loos, P., Riedl, R., Müller-Putz, G., vom Brocke, J., Davis, F. D., Banker, R. D., & Léger, P. -M. (2010). NeuroIS: Neuroscientific approaches in the investigation and development of information systems. *Business & Information Systems Engineering, 6*, 395–401.

Milic, N. (2017). Consumer grade brain-computer interfaces: An entry path into NeuroIS Domains. In: F. Davis, R. Riedl, vom Brocke J., P. M. Léger & A. Randolph (Eds.), *Information systems and neuroscience. Lecture notes in information systems and organisation* (Vol. 16). Cham: Springer.

Minas, R. K., Kazman, R., & Tempero, E. (2017). Neurophysiological Impact of Software design processes on software developers. In D. Schmorrow & C. Fidopiastis (Eds.), *Augmented cognition. Enhancing cognition and behavior in complex human environments. AC 2017. Lecture notes in computer science* (Vol. 10285). Cham: Springer.

Moon, J., & Kim, Y. (2001). Extending the TAM for a world-wide-web context. *Information and Management, 38*(4), 217–230.

Moore, M. M., Storey, V. C., & Randolph, A. B. (2005). User profiles for facilitating conversations with locked-in users. In

Proceedings of the international conference on information systems (pp. 923–936).

Moridis, C. N., Terzis, V., Economides, A. A., Karlovasitou, A., & Karabatakis, V. E. (2012). Integrating TAM with EEG frontal asymmetry. In *7th mediterranean conference on information systems* (*MCIS 2012*).

Ong, C., & Lai, J. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Computers in Human Behaviour, 22*(5), 816–829.

Randolph, A. B., Karmakar, S., & Jackson, M. M. (2006). Toward predicting control of a brain-computer interface. In *Proceedings of the international conference on information systems* (pp. 803–812).

Riedl, R., Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Dimoka, A., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Móller-Putz, G., Pavlou, P. A., Straub, D. W., vom Brocke, J., & Weber, B. (2010a). On the foundations of NeuroIS: reflections on the Gmunden Retreat 2009. *Communications of the AIS, 27*, 243–264.

Riedl, R., Hubert, M., & Kenning, P. (2010b). Are there neural gender differences in online trust? An fMRI study on the perceived trustworthiness of eBay offers. *MIS Quarterly, 34*(2), 397–428.

Ringle, C. M., Wende, S., & Will, A. (2005). *SmartPLS 2.0* (beta). University of Hamburg, Germany. http://www.smartpls.de.

Steiner, A.R.W., & Coan, J. A. (2011). Prefrontal asymmetry predicts affect, but not beliefs about affect. *Biological Psychology, 88*, 65–71.

Terzis, V., & Economides, A. A. (2011). The acceptance and use of computer based assessment. *Computers & Education, 56*(4), 1032–1044.

Terzis, V., Moridis, C. N., Economides, A. A. (2012). The effect of emotional feedback on behavioral intention to use computer based assessment. *Computers & Education, 59*(2), 710–721.

Urbach, N., & Ahlemann, F. (2010). Structural Equation Modeling in information system using Partial Least Square. *Journal of Information Technology Theory and Application, 11*(2), 5–40.

Venkatesh, V. (1999). Creation of favorable user perceptions: Exploring the role of intrinsic motivation. *MIS Quarterly, 23*, 239–260.

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*, 451–481.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Vom Brocke, J., Riedl, R., & Léger, P. M. (2011). Neuroscience in design-oriented research: Exploring new potentials. In H. Jain, A. P. Sinha & P. Vitharana (Eds.), *Service-oriented perspectives in design science research, Lecture notes in computer science* (Vol. 6629, pp. 427–439). Berlin: Springer.

Willems, R. M., Van der Haegen, L., Fisher, S. E., Francks, C. (2014). On the other hand: Including left-handers in cognitive neuroscience and neurogenetics. *Nature Reviews Neuroscience, 15*(3), 193–201.

Wilson, G. M., & Sasse, M. A. (2004). From doing to being: Getting closer to the user experience. *Interacting with Computers, 16*(4), 697–705.