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JOURNAL

Journal of Management Information Systems

DEPOSITED IN ORE

13 September 2019

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ABSTRACT

Behavioral beliefs – perceived usefulness and perceived ease of use – have been identified as the most influential antecedents of individuals' information systems use intentions and behaviors within the technology acceptance model. However, little research has been aimed at investigating the implicit (automatic or unconscious) determinants of such cognitive beliefs, and more importantly, the potential nonlinear relationships of such antecedents with explicit (perceptual) ones. As such, this paper theorizes that implicit neurophysiological states – memory load and distraction - and explicit – engagement and frustration - antecedents interact in the formation of perceived usefulness and perceived ease of use. In order to test the study's hypotheses, we conducted an experiment that measured neurophysiological states while individuals worked on instrumental and hedonic tasks using technology. The results show that, as theorized, implicit and explicit constructs interact together, and thus, have a nonlinear effect on behavioral beliefs. Specifically, when engagement is high, neurophysiological distraction does not affect perceived usefulness, whereas when engagement is low, neurophysiological distraction has a negative and significant effect on usefulness. The results also show that when frustration is high, neurophysiological memory load has a negative effect on perceived ease of use, whereas when it is low, neurophysiological memory load has a positive effect on perceived ease of use. This study makes several contributions, including the demonstration of the importance of emotional perceptions for moderating the effects of neurophysiological states on behavioral beliefs.

Keywords: NeuroIS, IS acceptance, IS use, behavioral belief formation, cognitive beliefs, electroencephalography (EEG), non-linear effects, emotion, TAM.

Note: All authors contributed equally to this paper.

"Beliefs are mental objects in the sense that they are embedded in the brain"

Kathleen Taylor, neuroscientist at Oxford University [63]

INTRODUCTION

Understanding whether individuals decide to use a given technology is critical as companies invest significant resources in Information Systems (IS). Reflecting this, most research on IS has been aimed at explaining such acceptance decisions. For example, users' intentions to use a given technology are influenced by how useful and easy to use they believe the technology to be [38]. Despite suspicions of common method bias on IS acceptance research [110, 119], these two behavioral beliefs – perceived usefulness (PU) and perceived ease of use (PEOU) - have become two of the most researched constructs in IS research [e.g., 16, 27, 28, 37, 48, 59, 60, 68]. Thus, behavioral beliefs are valuable in general because they are able to give some insight into important questions [12] such as whether a given technology will be used.

Given the criticality of behavioral beliefs for the IS field, researchers have argued that their antecedents need to be identified and investigated [12, 15] in order to understand how such beliefs are produced [10]. Further, scholars have recommended that in order to identify such antecedents, a fresh look at the original theories of reasoned action (TRA) and planned behavior (TPB) need to be taken [12]. As a result, since the late nineties, researchers have looked at these theories and identified a wide range of cognitive and emotional factors that influence such beliefs [3, 11, 66]. All of these factors have one thing in common: they are all explicit. In other words, they are perceptual factors of which individuals are aware of and can report.

The common (or exclusive) focus on explicit antecedents has three major limitations that stem from the fundamental link between the theoretical meaning of a construct and its empirical observation [10]. First, because explicit antecedents are perceptual, past research has asked users to reflect on use (via the self-reported measures) before or after the use experience, thus, *omitting the potential influence that mental activities during actual IS use* might exert on subsequent behavioral beliefs [83]. Second, the exclusive use of self-reported measures *cannot capture automatic mental states that might occur outside individuals' awareness* [79, 83] and that might play a role in determining behavioral beliefs [45]. In fact, the TRA and TPB literatures explain that explicit antecedents can only provide an incomplete picture of the formation of behavioral beliefs [34] and that implicit (i.e., automatic or unconscious) antecedents need to be studied as well. With the introduction of neuroscientific tools to the IS field [e.g., 42, 99], researchers are being encouraged to utilize these tools to identify implicit antecedents of IS constructs [43], and as such, localize how implicit factors can affect such beliefs [45]. Finally, several researchers have pointed out that, due to the exclusive focus on self-reported measures, *IS acceptance research is likely to suffer from common method bias* [110, 119]. This results in the possibility that methodological artifacts bias the estimates of the relations between the different constructs [110, 119]. Thus, there is a need to combine structurally different methods - by measuring implicit antecedents via neuroscience tools along with explicit ones via self-report – in order to overcome common method bias concerns [82].

In order to address these three limitations, this study aims to investigate the following research questions: 1) what are the implicit antecedents of perceived usefulness (PU) and perceived ease of use (PEOU)? and 2) how do implicit (i.e., memory load and distraction) and explicit (i.e., engagement and frustration) constructs interact in determining behavioral beliefs? The rest of the paper is organized as follows. First, a succinct review of the theoretical underpinnings of the Technology Acceptance Model (TAM) is presented. Second, the theoretical justification for the interaction of implicit and explicit measures in determining behavioral beliefs is developed. Third, we explain the methodology – an experiment – as well as its results. Finally, we end the paper by providing insights for theory, research, and practice.

BEHAVIORAL BELIEFS IN IS ACCEPTANCE RESEARCH

Behavioral beliefs are key constructs of TAM, a model often used to explain or predict IS acceptance [15]. The original TAM [38, 39] was founded on the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB). Behavioral beliefs are key constructs in these theories [6-8, 50], and have been replaced within TAM by PU, "the degree to which a person believes that using a particular system would enhance his or her job performance", and PEOU, "the degree to which a person believes that using a particular system would be free from effort" [38, p. 320]. TAM advances that IS acceptance/use is determined by the behavioral intention to use a system. Intention, which is influenced by attitudes towards the behavior (a construct later excluded from the model), is influenced by the two core behavioral beliefs of PU and PEOU. PEOU also influences intentions indirectly through a positive relation to PEOU. Finally, both PU and PEOU are posited to be formed by external variables, which were not specified in the original model. The core of the TAM model is shown in Figure 1.

--------- Insert Figure 1 here ---------

Antecedents of Behavioral Beliefs

While research based on TAM has advanced our understanding of how behavioral beliefs influence IT acceptance and is thought to have reached iconic status in IS acceptance [131], several researchers have expressed concerns about different aspects of this stream of research (e.g., falsifiability, treating behavioral beliefs as 'black boxes', and common method bias; please see [15, 110, 113, 119] for more details). All in all despite such concerns, the impression is that TAM does have some predictive power and with the objective of better understanding its antecedents, the field needs to explore why users perceive a system to be useful or easy to use [15, 45].

These calls for research on the antecedents of behavioral beliefs include recommendations to return to the original TRA and TPB, with the hope of discovering the building blocks of behavioral beliefs [15]. As a result, IS research has turned to the original TRA and TPB to investigate how behavioral beliefs are formed and thus, identify antecedents to the formation of such beliefs [66]. More specifically, IS research has identified a wide range of antecedents to behavioral beliefs. On the one hand, cognitive constructs such as social presence, social influence, perceived accessibility, and availability of user training and support have been proposed and studied as factors affecting cognitive beliefs [e.g., 66]. On the other hand, more emotional constructs such as those capturing states related to frustration, psychological ownership and engagement, have been linked to behavioral beliefs [e.g., 2, 11, 103, 129]. Furthermore, such states have been associated with particular design features of technologies or specific experiences occurring while using technologies [e.g., 26, 70, 133], thus suggesting a relation between these emotional states and beliefs about the technology.

All these antecedents identified by the IS literature are *explicit* or perceptual: they represent phenomena that occur within individuals' awareness and as such, individuals can report on them. However, the literature in TRA and TPB has also identified *implicit* determinants (i.e., unconscious or automatic) of behavioral beliefs [6, 8]. These implicit antecedents exist and have been observed in various non-IS contexts [e.g., 5, 46, 112]. Scholars note that implicit and explicit antecedents may not relate because people cannot report accurately on things about which they might be unaware [84]. In the specific case of IS research, research on implicit antecedents of behavioral beliefs is non-existent with the notable exception of Dimoka, Pavlou and Davis' paper [45] on the neural correlates of PU and PEOU. Thus, as it will be shown next, complementing Dimoka et al.'s efforts is important because it is argued that by not studying both explicit (i.e., perceptual) and implicit (i.e., unconscious or automatic) antecedents of behavioral beliefs in IS research, we have a) only partially captured the formation of such beliefs [34], and b) built a research stream that is likely to suffer from common method bias [110, 119].

In sum, past research on IS acceptance is limited because it says little about 1) the relative effects of implicit vs. explicit antecedents of beliefs, and 2) the potential interaction between explicit and implicit constructs affecting behavioral beliefs. As such, uncovering the explicit and implicit antecedents of behavioral beliefs can provide finer grained knowledge about the determinants of individual IT acceptance and use.

THEORETICAL DEVELOPMENT

This section serves to establish the links between both implicit (neurophysiological, or neural) and explicit (perceptual) antecedents of behavioral beliefs and their potential interaction (see Figure 2).

--------- Insert Figure 2 here ---------

Implicit Antecedents of Behavioral Beliefs

Implicit (or neural) approaches to the investigation of behavioral beliefs can complement current approaches because they address some of the limitations of IS acceptance research identified earlier. First, they allow for the capture of users' reactions to technology as they occur in real time while users actually interact with the system [83]. This is important because beliefs are formed as experiences take place. Second, they can capture 'unconscious' or 'automatic' processes that occur outside individuals' awareness [42, 45, 79] and thus, provide a more complete view of what actually takes place within the brain while behavioral beliefs are formed.

Third, because implicit antecedents need to be captured using different methods (e.g., neurophysiological tools) than those used for measuring explicit ones (e.g., self-reports), the combination of structurally different methods serves to reduce the common method bias often suspected in IS acceptance research [80, 119].

Research on the implicit antecedents of behavioral beliefs is non-existent except for a recent illustrative fMRI (functional magnetic resonance imaging) investigation by Dimoka and colleagues[1] [45]. In their paper, Dimoka et al. although not looking for antecedents of behavioral beliefs but for their neural correlates, found that PU correlated with the activation of the caudate nucleus and the anterior cingulated cortex. The caudate nucleus and anterior cingulated cortex are activated by large rewards [61, 76] and the anticipation of rewards [40] respectively. Dimoka and colleagues also found an association between PEOU and the prefrontal cortex [45], an area of the brain associated with memory load, such as cognitive effort and working memory [20].

In the present research, we use EEG (electroencephalogram) to assess implicit antecedents of behavioral beliefs - the measures are explained in more detail in the Methodology section - and thus, complement previous efforts on the identification of neural correlates of IS behavioral beliefs [e.g., 45]. The use of EEG builds upon and complements Dimoka et al.'s [45] research in several meaningful ways. First, unlike studies using fMRI, EEG allows for the recording of electrical signals generated within the brain's outer layer (the cerebral cortex) [92] *while* users *actually interact* with the system to work on a task. In contrast, the Dimoka et al. [45] study conducted the fMRI recording when the items of PU and PEOU were shown to participants, and thus, after participants' interaction with the system. As such, this usefully

[1] [1] A related paper by Dimoka and colleagues was presented earlier at a major IS conference [44].

complement fMRI studies by adding realism to the investigation and by capturing brain-related electrical signals as technology interactions take place. Second, because of the timing of fMRI measurement – when individuals where shown the PE and PEOU items – the objective of Dimoka et al. [45] was to look for implicit correlates of PE PEOU, and not for its implicit antecedents, which is the objective of our study. Third, EEGs produce finer temporal resolution than fMRI [87] which provides more detailed parameters of the electrical cerebral activity during actual IS interactions. Thus, the present study investigates the neural antecedents of PU and PEOU with the use of EEG.

Implicit Distraction

Because the literature on IS has argued for a relation between attention-related constructs (e.g., cognitive absorption) and usefulness [e.g., 3, 11], this study investigates distraction (D) as an antecedent of PU. Distraction can be considered as a state of "deploying attention away from the emotionally salient aspects of an emotion-eliciting event" [123, p. 84]. Within the EEG literature, this is measured with a combination of relative and absolute power spectra from several EEG sites (please see the Methodology section for a more detailed explanation of the distraction measure). Such a state is different from explicit (i.e., perceptual) attention-related constructs (e.g., cognitive absorption and engagement) found in the IS literature [e.g., 3, 103, 133] in several ways: 1) it does not include a pleasurable component, 2) it is concerned with one's capability to remain focused and effectively respond to stimuli rather than one's mental immersed state, 3) it does not have a temporal dissociation component, and 4) it does not have an intrinsic interest or curiosity component.

By building upon the neuroscience literature, we argue for a negative relation between distraction and PU for several reasons. When using a given technology, the system needs to provide relevant and useful information so that the user remains focused and alert while interacting with the system, ensuring situation cognizance [95]. Situation cognizance refers to the intellectual grasp of a situation so that the technology supports the user's informed action [95]. As such, if a system ensures situational cognizance by capturing the user's attention and providing the required information for the accomplishment of the task, then the user will perceive the system as useful. That is, if a system is capable of diminishing the user's distraction by providing relevant information [95] then the user will be able to better perform the task, eventually perceiving the system as more useful.

It is important to note that attention decrements are normal in technology-related tasks as time goes by and are associated with repetitive observations [51]. Thus, if technology is capable of providing relevant information for the task being performed, the distraction will remain low over time, allowing the individual to focus his attention on the task [51]. If this is the case, the user will perceive the system as useful because it allows him to fully concentrate on the task for which the technology is being used.

The literature has also found significant correlations between different EEG-based indices measuring distraction-related states (such as alertness and vigilance) and performance [19, 21, 73-75]. That is, this research indicates that the less the distraction, the more the performance in a given task. We expect this to relate to PU, as PU represents an instrumental belief entailing an evaluative process about the performance of a technology to reach an outcome. Because performance increases when distraction lowers, we can therefore expect that the less distracted a person, the better the performance, and the more useful s/he will perceive the technology. Thus:

Hypothesis 1: Distraction (D) negatively relates to PU.

Implicit Memory load

Taking Dimoka et al.'s [45] results as a starting point, we theorize that memory load (ML) will relate negatively with PEOU. We define ML as the demands placed on working memory while performing a given task [86]. ML is usually measured by the brain (electrical) activity occurring in the frontal midline (Fz) for the theta frequency (4-7Hz). This frontal midline activity has been consistently reported to be involved in human working memory [57, 62, 106] (see the Methodology section for details).

By drawing upon the literature on neuroscience and IS, we posit that memory load will relate to PEOU for several reasons. First, memory load indicates cognitive strain. Cognitive strain is "affected by both the current level of effort and the presence of unmet demands" [65, p. 59]. Thus, as memory load increases so does cognitive strain. Cognitive strain is in the opposite side of the spectrum of cognitive ease: a sign indicating that there is no need for the mobilization of effort [65]. The shift from cognitive ease to cognitive strain makes users switch to an analytic mode of effortful mental activities [65]. If, when interacting with a system, a user experiences memory load, this implies that cognitive strain has occurred and thus, that an effort is required for the use of the technology, hence perceiving the technology as less easy to use.

Second, recent research has found that certain types of computer interfaces lead to better PEOU [104], suggesting that design features influence demands on working memory. That is, good design eases memory load [120]. As such, when memory load is low, PEOU increases, implying a negative relationship between memory load and PEOU.

Finally, some view PEOU as the converse of complexity (when using a system) [39]. Interestingly, complexity is also related to the notion of intrinsic cognitive load [54] or the "amount of informational units a learner needs to hold in working memory to comprehend information" [24, p. 54]. Thus some equate the complexity of a task with the memory load required to accomplish it [85]. As a result, one can deduce that memory load would relate negatively to PEOU. As such:

Hypothesis 2: Memory load (ML) negatively relates to PEOU.

Explicit Antecedents of Behavioral Beliefs

In addition to the implicit antecedents of PU and PEOU, it is also important to consider their explicit (perceptual) antecedents. As argued above, including both implicit and explicit antecedents of behavioral beliefs provides a more complete picture of the formation of behavioral beliefs. Methodologically, including only one independent variable for each behavioral belief may inflate the relation between the independent and dependent variables due to a lack of competition with other potential independent variables in explaining the outcome. In order words, this is critical to rule out rival explanations that might threaten the internal validity of the findings[2] [31]. As a result, we posit that explicit engagement (E) and frustration (F) will influence PU and PEOU, respectively.

Engagement and PU

Engagement (E), a flow-related construct capturing an individual's state of pleasure and absorption while performing a task, has been found to influence performance and future intentions to use a given technology [133]. Related constructs, such as cognitive absorption, have also been found to influence PU beliefs [2, 103]. The notions of cognitive absorption and engagement have the same theoretical underpinnings[3]: both emphasize focus of attention, pleasure, and intrinsic interest and curiosity as dimensions of the constructs [4, 133].

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[2] We thank an anonymous reviewer for this insight.

[3] In line with Webster and Ahuja (2006, p. 665), the construct of engagement was included in our study for the main reason that our respondents were asked to perform directed tasks that lasted only 10 minutes, which is not enough

The argument for a relation between E and PU is based on self-perception theory [2, 14, 103]. If a user is cognitively engaged in using a given technology, s/he experiences pleasure from that activity. Because such pleasurable experience is often at odds with an instrumental use of technology, the user experiences cognitive dissonance [2]. According to self-perception theory, such cognitive dissonance needs to be resolved by the individual [14]. The resolution occurs when the individual rationalizes the pleasurable experience as useful. As a result, this theoretical rationale would argue for a positive relation between E and PU.

Hypothesis 3: Engagement (E) positively relates to PU.

Frustration and PEOU

Researchers have argued that PEOU is influenced by several emotion-related constructs such as computer anxiety [129]. The idea behind these links is that emotional experiences with a given technology play a role in determining its PEOU. Based on this research, we posit that frustration while using a given technology will influence PEOU. Frustration can be defined as an emotional response to situational opposition [23]. That is, frustration arises when individuals perceive a situational opposition, beyond their control, that prevents them from accomplishing their goals [23]. General theories of anxiety would suggest a negative link between frustration and PEOU[4] [e.g., 91]. Such theories state that frustration produces cognitive reactions that are likely to impact expectancies of a given situation [91]. That is, if a person is frustrated while using a given technology because it does not allow him/her to easily complete the task, it is likely that s/he will not perceive the technology as easy to use.

time to experience the user "control" dimension which would have allowed us to use the construct of cognitive absorption (please see Agarwal and Karahanna 2000, p. 672).

[4] Please see Riedl [97] for an exhaustive review on the biology of technostress.

Furthermore, researchers have argued that ease of use reduces users' frustration [32, 70], and that usability of a website reduces frustration which increases ease of use [96]. Furthermore, the literature on computer education has pointed out that students often become frustrated when they cannot understand a given technology [132]. Thus, frustration is important in determining the PEOU about a certain technology. As such:

Hypothesis 4: Frustration (F) negatively relates to PEOU.

Interactions between Explicit and Implicit Antecedents of Behavioral Beliefs

Until now we have considered the 'main effects' of each explicit and implicit construct on behavioral beliefs. However, when we have two independent variables (e.g., ML and F) influencing a dependent one (e.g., PEOU), there is more to consider than main effects [84]. Two independent variables can also influence the dependent variable in combination, suggesting an interaction effect [49]. This represents a possibility in the case of implicit and explicit antecedents of behavioral beliefs. As described earlier, explicit measures may be unrelated to implicit measures of the same phenomenon because the latter also includes automatic processing outside individuals' awareness. For example, people tend to underestimate stress; that is, their perception of stress does not correlate with actual elevations of stress hormones [128]. Thus, to the extent that implicit measures (e.g., D and ML) can capture states of which the individual might be unaware, and given that behavioral beliefs (PU and POU) are judgment calls of a given experience, we posit that individuals' perceptions of their experiences with technologies will moderate the relation between implicit measures and behavioral beliefs. As a result, we propose that engagement and frustration will moderate the relationships between D and PU and ML and PEOU, respectively.

Interaction between Engagement and Distraction on PU

Because we argued that distraction should relate negatively to PU, it is logical to think that other perceptual constructs that include pleasurable dimensions (e.g., engagement) might moderate the relation between D and PU. Because engagement captures the perception of the experience with a given technology and thus represents a description of what the user consciously experiences, it should moderate the relation between the distraction construct and PU. That is, if the user perceives that s/he was engaged while using the technology, the negative relation between D and PU is attenuated. In contrast, if the user perceives that s/he was not engaged while using the technology, the negative relation between D and PU is strengthened. As a result:

> **Hypothesis 5:** Engagement (E) moderates the negative relation between distraction (D) and PU. More specifically, the negative influence of D on PU weakens as engagement (E) increases.

Interaction between Frustration and Memory Load on PEOU

We posit that frustration will moderate the relation between ML and PEOU. Because ML is an implicit measure that can also capture memory load of which the user might be unaware, we propose that perceptions of frustration will serve to moderate the relation of implicit ML and PEOU. More specifically, when frustration is high, the relation between ML and PEOU will be negative, whereas when frustration is low, the relation between ML and PEOU will be positive.

Under low frustration, ML will positively influence PEOU. Indeed, mediofrontal theta oscillations have been shown to increase in the context of positive behavioral adaptation [25]. In other words, when behavioral adaptation is facilitated through positive feedback – or absence of negative events leading to frustration – an individual will feel that s/he is making good progress and thus perceive the system as easy to use. In contrast, high frustration will impede positive behavioral adaptation and thus ML will have a negative effect on perceptions of ease of use.

This relationship is also consistent with cognitive load theory [33] which posits that learning occurs when the capacity of the working memory does not exceed the requirements of the task. That is, when learning is not detracted by task- or technology-related factors that would overwhelm memory load, an individual will pursue his learning process and thus perceive the system as easy to use. Alternatively, high frustration is likely to affect memory load and hence cause ML to have a negative effect on ease of use perceptions. As such:

> **Hypothesis 6:** Frustration (F) moderates the relation between memory load (ML) and PEOU. More specifically, when F is high the relation between ML and PEOU is negative whereas when F is low the relation between ML and PEOU is positive.

RESEARCH METHODOLOGY

A double-blind experiment[5] was conducted in order to investigate the effects of implicit and explicit antecedents of PU and PEOU. Twenty-four upper-year undergraduate students took part in the experiment. The students were between 20 and 25 years old and were recruited from a homogenous student population at a university business school. Participants were screened for neurological and psychiatric disorders, as well as for attention deficit disorder. Participants were also asked not to use any attention enhancing substances prior to the experiment. This sample size is comparable with sample sizes in other NeuroIS research [45, 98, 100] and in leading neuroscience journals [72].

Participants were asked to perform two experimental tasks of ten minutes each: an instrumental one using Access, and a hedonic one using educational gaming software. There were two main reasons for two different tasks. First, there are theoretical grounds for differences between hedonic and instrumental tasks when using technologies [78, 126]. For instance, recent research has found different brain areas associated with PU when using a real (instrumental)

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[5] The experimental administrator and participants were unaware of the hypotheses of the study.

website and when using a fictitious one [45]. Second, the experimental design is stronger methodologically with the addition of a second task. If participants performed only one task, the variables of interest, PU and PEU, might not have a lot of variance, resulting in a too narrow a range [108]. This possibility poses a threat to internal validity by both lowering the power of the tests and weakening the relations in which these variables participate [108].

Protocol

Participants arrived at the laboratory and were greeted by the experimental administrator. While participants read the information letter and consent form, the experimental administrator ensured that the neurophysiological equipment (EEG headset, etc.) was ready for utilization. After the consent form was signed, the experimental administrator placed the EEG sensors and the wireless headset on the participant's head. The B-Alert headset uses silver-silver chloride sensor sites interfaced with 100 ppi foam. As suggested by the manufacturer, we used a highly conductive electrode cream (Synapse). Impedance levels were tested at the beginning and at the end of the recording. The B-alert software automatically highlights impedance values that are higher than the recommended levels [1]. On average initial impedance checks took between 5 to 10 minutes. While the B-Alert is designed for 7 to 9 hours of continuous use, in our experiment the recording did not last more than ten minutes per task.

After the impedance tests, participants completed a standard 15-minute baseline test developed and validated by the manufacturer of the EEG headset [18]. This baseline test is important because it allows the data captured by the EGG sensors to be adjusted by the software to accommodate for individual differences in EEG recordings [1]. After this, participants were asked to complete the experimental tasks.

As it will be explained next, the neurophysiological measures (D and ML) were recorded while participants used a given IT to accomplish the experimental tasks. In contrast, the measures of PU, PEOU, E, F, and Intention were captured via a questionnaire administered after each experimental task was completed.

Measures

Description of explicit measures

Self-reported measures of engagement, frustration, PU, PEOU and intention that have been used in past IS research and that are well established in the field were adopted for this study. Engagement was captured by the engagement scale developed by Webster et al. [135], which has been consistently used in the IS literature [e.g., 133, 134]. Frustration was measured via the original scale developed by Peters et al. [88]. PU, PEOU and intention (I) were adopted from Venkatesh and Davis [130]. All measures are reported in the Appendix.

Description of implicit measures

We used EEG to measure distraction and memory load for two main reasons. First, as described earlier, EEG complements fMRI approaches used in previous IS research by allowing for the recording of brain electrical activity while the user interacts with a technology. Second, due to good temporal resolution, changes in the oscillation of EEG signals can “accurately reflect subtle shifts in alertness, attention, and workload that can be identified and quantified on a second-by-second time-frame” [17, p. B232].

EEG is a technique for recording the oscillations of brain electrical potential related to cortical activity [77]. By placing electrodes on the scalp of a research participant, the EEG sensors amplify and acquire the electrical activity that originates in the cerebral cortex. Spectral analyses are used to estimate the contribution of various sinusoidal waves (with different frequencies and amplitudes) in the waveform of the EEG signals. Using a Fast Fourier Transformation, the strength of the signal is quantified by the power of the signal (i.e., the root-mean-square of the average amplitude) at the given frequency or range of frequency. The most common range of frequencies of bands utilized in EEG research are delta (1-4Hz), theta (4-8), alpha (8-13Hz), beta (13-30Hz) and gamma (36-44Hz) [92].

D and ML were obtained via the B-Alert® X10 device from Advance Brain Monitoring [1]. This wireless device does not restrict participants' movements; thus, it allows for the recording of high quality and real time EEG data while participants use technologies in a relative realistic manner. The B-Alert uses a headset with 9 sites (F3, F4, Fz, C3, C4, Cz, P3, P4, and POz).

D was measured via an index that calculates the probability of the individual being distracted, based on previous literature on attention, vigilance, and alertness [e.g., 51, 95]. This literature has calculated distraction related measures by combining frequency bins in the theta, alpha and beta bands. The overall assumption is that a direct relationship exists between beta and distraction (or alertness), while alpha and theta are inversely related [107]. Building upon this literature, Berka et al. [17] developed a four-class 'alertness' index. Using a quadratic discriminant functional analyses, the index is calculated using absolute and relative power spectra from channels FzPOz and CzPOz of the theta, alpha, and beta frequencies (the specific Hz bins used in the DFA are explained in more detail in [17, 19, 64]). The index reflects information-gathering, visual processing and allocation of attention [17]. As a result, we took the 'distracted' component of the four-level 'alertness' index in order to measure D. It is important to note that these measures have been validated empirically [17, 64] and used in several neuroscience studies [e.g., 93, 116].

ML was measured by the brain electrical activity occurring in the frontal midline (Fz) for the theta frequency (4-7Hz). Research has consistently shown that frontal midline (Fz) activity in the theta frequency is involved in memory load [56, 62, 106]. Thus, changes in the theta-band at Fz are associated with working memory tasks: the theta band at the site increases in power from tasks involving low memory load to tasks involving high memory load [57]. As memory load increases, there is an increase in frontal theta activity [62]. Evidence from magnetoencephalology also confirms the modulation in frontal theta activity with memory load demands [122].

Finally, it is important to note that EEG recordings often include signal distortions called artifacts. These artifacts occur as a result of eye movements and muscular contractions and need to be identified and removed from the data [121]. The B-Alert software uses a patented artifact identification and decontamination algorithm [71] which identifies and removes 5 types of artifacts: tonic muscle artifacts, eye blinks, excursions, saturations, and spikes [125]. EEG data is automatically rejected when movement level data, captured by the accelerometer, exceeds unacceptable thresholds. Accordingly, one-second periods including artifacts were removed automatically from the data by the B-Alert wireless headset before D and ML calculations.

RESULTS

The results are reported in the following two sections. First, we report the psychometric properties of the measures capturing the constructs of interest. Second, the results with respect to the hypotheses are presented.

Properties of the Measures

Before testing the hypotheses, the psychometric properties of the measures were evaluated. First, as shown in Table 1, all loadings were above the recommended threshold of .6

[53] except for three items of Engagement (E1, E2 and E3) that were dropped from the scale[6]. The loadings of all construct were also higher than their cross-loadings on all other constructs hence demonstrating good discriminant validity between the study's constructs. Furthermore, the correlations among all the measures (self-reported and neurophysiological) were below .50, and the square roots of all AVEs were larger than inter-construct correlations providing further evidence for discriminant validity among all measures [29]. Additionally, as shown in Table 2 , the self-reported measures of PU, PEOU, I, F, and E had good reliability, above the .80 cutoff recommended for management research [69]. Finally, in order to assess multicollinearity, variance inflation factors (VIFs) were estimated and were all below the recommended threshold of 3.3 [41] thus showing that multicollinearity is not likely to have affected the results (see Table 2).

--------- Insert Tables 1 and 2 here ---------

Besides the impedance tests performed before the recording of the EEG data ensuring the reliability of the data, we also established the construct validity of these measures through nomological validity as indicated by Straub et al. [118]. Because EEG measures related to distraction and memory load have been consistently linked to performance [19, 21, 22, 55, 56, 74, 75, 115, 136], we ran a model specifying both D and ML as antecedents of participants' performance in the experimental tasks. This test ensured that the D and ML supported the same results as those reported in the neuroscience literature. Our tests indicated that both D and ML were significantly related to performance in both the instrumental and hedonic tasks, consistent with the EEG literature. Thus, our findings, convergent with those of the neuroscience literature, ensure the construct validity of the EEG measures [118].

[6] In order to mitigate the risk of model over-specification [53], we ran all analyses with and without the deleted items E1, E2 and E3, and found no change in the significance of the path coefficients.

Test of the Research Model

Consistent with recent IS research [e.g., 67, 114, 127], SmartPLS 2.0 [102] was used for the analysis of the research model. PLS was chosen as the structural equation modeling method of this paper because of the study's exploratory nature - i.e., for the reason that it is the first study that hypothesizes and tests the main and interaction effects of explicit and implicit antecedents of behavioral beliefs. With respect to our *main effects model* and as shown in Figure 3, our results support the majority of the study's hypotheses[7]. First, the path coefficient from D to PU was negative and significant ($\gamma = -0.51$, $p < 0.001$) supporting H1. Similarly, the path coefficient from ML to PEOU was negative and significant ($\gamma = -0.42$, $p < 0.001$) supporting H2. However, H3 was not supported as shown by the non significant coefficient from PE to PU ($\gamma = 0.009$, $p > .05$). Finally, the path coefficient from F to PEOU was negative and significant ($\gamma = -0.41$, $p < 0.001$) supporting H4. The implicit (D) and explicit (E) measures explained 31% of the variance in PU, while the implicit (ML) and explicit (F) measures explained 38% of the variance in PEOU (see Figure 3).

--------- Insert Figure 3 here ---------

With respect to the *interaction or nonlinear effects – the main focus of this paper* -, all the hypotheses were supported. As shown in Figures 4 and 5, the interaction coefficient between D and E was positive and significant ($\gamma = 1.48$, $p < 0.001$) supporting H5 and indicating that the negative influence of D on PU weakens as engagement increases. Moreover, the interaction coefficient between ML and F was negative and significant ($\gamma = -1.38$, $p < 0.001$) supporting H6 and indicating that when frustration is high the relation between ML and PEOU is negative

[7] Given that the paper's main objective was to evaluate the implicit and explicit determinants of PU and PEOU, we did not formally hypothesize the effects of PU- PEOU on intention as well as the effect of PEOU on PU. The estimates of such relationships are however shown in Figures 3 and 4.

whereas when frustration is low the relation between ML and PEOU is positive (see Figures 4 and 6). This model including interaction effects explained 37% of the variance in PU and 39% of the variance in PEOU; this represents a significant increase in the explained variance in PU ($\Delta R^2 = 5\%$) and a slight increase in the explained variance in PEOU ($\Delta R^2 = 1\%$) when compared to the 'main effects' model.

--------- Insert Figures 4, 5 and 6 here ---------

In order to get a deeper understanding of the interactions between D and E, and between ML and F, we conducted a partial derivative analysis [94, 124] as shown in Tables 3 and 4.

--------- Insert Tables 3 and 4 here ---------

The coefficient of D shows the relationship between distraction and PU holding engagement constant, and represents the partial derivative of PU with respect to E. As can be seen in Table 3, when engagement is high, D has no statistically significant effect on PU, whereas when E is low, D has a negative and significant effect on PU.

In the same vein, the coefficient of ML shows the relationship between memory load and PEOU holding frustration constant, and represents the partial derivative of PEOU with respect to F. As can be seen in Table 4, ML has a significant effect on PEOU only at very high or very low levels of frustration; that is, it has no statistically significant effect at mid-range levels of frustration. In other words, when frustration is very high, ML has a statistically significant negative effect on PEOU, whereas when frustration is very low, ML has a statistically significant positive effect on PEOU.

Finally, given the relatively low sample size of the study, we computed the effect sizes of PU and PEOU's antecedents, as well as the cross-validated redundancy measures Q^2 of E, D, F, ML, PU, PEOU and I to assess the model's predictive relevance [53, 101]. Effect sizes are important because they provide an indication of the strength of the relation between a given (or a set of) independent variable(s) and a dependent one [111]. Thus, effect sizes provide complementary information to that of significance tests [30]. As shown in Table 5, Cohen's effect size (f^2) estimates show large and medium effects of the implicit (neurophysiological) antecedents, D and ML, on PU and PEOU respectively, as well as small effects of the interaction between implicit and explicit measures on PU and PEOU. Lastly, the cross-validated redundancy measures Q^2 of E, D, F, ML, PU, PEOU provided by the SmartPLS 2.0 blindfolding report were all significantly above zero and were respectively 0.49, 1.0, 0.75, 1, 0.34, 0.30 and 0.30 hence providing support for the model's predictive relevance [58].

--------- Insert Table 5 here ---------

DISCUSSION

Understanding how individuals decide to use (or not) a technology is a crucial question in IS research. Behavioral beliefs are well-established antecedents of individuals' use intentions (and behaviors) with a given technology. However, an important gap in this research stream is its silence with respect to the implicit determinants of behavioral beliefs and their interaction with explicit ones. Thus, the main objective of this study was to investigate the role of implicit and explicit constructs in the formation of behavioral beliefs. Our revision of the theoretical underpinnings of TAM, TRA and TPB, suggests that both implicit and explicit constructs should play an important role in determining IS behavioral beliefs. Our results are consistent with this suggestion and support the proposed interaction hypotheses, thus, making several theoretical contributions.

First, this paper represents a first effort in identifying how two important behavioral beliefs (i.e., PU and PEOU) are implicitly formed during the accomplishment of a task using a given technology. Indeed, identifying the implicit antecedents of behavioral beliefs during IS use is important for two main reasons. First, it allows tapping into the content of such beliefs and hence provides a deeper understanding of the mechanisms leading to IS use behaviors [9]. Second, it allows unraveling the mechanisms by which specific 'external variables' (to TAM) experienced during technology use influence behavioral beliefs and thus, provides valuable information into how to 'manipulate' such behavioral beliefs [15], as it is explained later in the practical implications.

Second, our study demonstrates that explicit (i.e., perceptual) and implicit (i.e., neurophysiological) measures influence behavioral beliefs in a nonlinear and complex way. Conceptualizing nonlinear relationships is important because it provides a more accurate explanation of complex phenomena [124]. This is particularly relevant in the context of TRA/TPB based IS acceptance models given that theory grounded operationalization of nonlinear effects between antecedents of behavioral beliefs represents a strong avenue to extending the explanatory power of such models [9]. In fact, "*the problems with most tests of moderating effects to date are that little theoretical insight is provided into the mechanism, or "the why", behind proposed interaction effects [...] making such broadenings of TAM both unwieldy and conceptually impoverished"* [9, p. 244]. As such, an important contribution of this study is that it provides new conceptual insights into the complex moderating effects of explicit measures on the relationships between implicit ones and behavioral beliefs.

Third, the hypothesized and supported interaction between perceived frustration and memory load provides an additional theoretical insight into the theoretical dangers of overlooking non linearities. Simply by hypothesizing and testing exclusive linear effects (see Figure 3), one could have mistakenly concluded that the effect of ML on PEOU is always negative. However, by theorizing upon adaptive learning [25, 33] and modeling the interaction between ML and perceived frustration (see Figures 4 and 6, and Table 4) we observe that this is not the case. In fact, the direction of the relation between ML changes depending on the values of perceived frustration. More specifically, the relation between ML and PEOU is negative when frustration is very high; it becomes non-significant for the middle range values of frustration; and it becomes positive when frustration is low. As such, the effect of ML on PEOU exhibits three different patterns which could not have been detected via an additive linear model. Therefore, such result points to the fact that the users' perceptions of experience with a given technology can change the direction in which neurophysiological states affect evaluative judgments about the technology.

Fourth, the interaction between engagement and distraction also contributes to theory: perceptions of engagement during a computer task moderate the effect of distraction on PU. More specifically, as engagement increases in value the relation between D and PU weakens, eventually becoming statistically non-significant. As such, perceptions of use experiences with technology are capable of moderating the effects of measures that can capture unconscious or 'hidden processes' of the same experience. This is important because it points out to the necessity of including both explicit (perceptual) and implicit (neurophysiological) constructs in order to have a more complete theoretical view of how evaluations of technology are formed.

Fifth, our results also contribute to the emerging field of NeuroIS. Within this emerging field, calls have been made to look for the neurophysiological antecedents of IS related constructs [45]. Our results show that such efforts should be combined with traditional approaches capturing explicit constructs to better explain such IS related constructs. To the extent that behavioral beliefs are evaluative judgments about a given technology, and taking into consideration individuals' tendency to be consistent about the world [105], behavioral beliefs will always, to a certain extent, be influenced by explicit (perceptual) evaluations of the experience with the technology.

Finally, our results point to the often overlooked theoretical importance of emotional experience in models explaining deliberative decision-making derived from TRA and TPB, such as TAM. Both frustration and engagement are emotional constructs, and our results are consistent with neuroscience and psychological research emphasizing the criticality of emotions for behavioral beliefs, everyday decision making, and rational choice [e.g., 35, 36, 47, 52, 90]. The influence of emotions on behavioral beliefs is an instance of the broader role that emotions play in human life by prioritizing between needs and directing actions [52]. Our results suggest that emotional experiences during use are capable of moderating the effects of neurophysiological measures on behavioral beliefs, by attenuating the strength of such relations or by changing their direction altogether. Thus, if we want to fully understand the reasons by which people believe a given technology is useful and easy to use, we need to also include and explore the emotional reactions that such technology triggers [13].

Methodologically, our study also contributes to the IS field in several ways. First, the use of EEG complements fMRI approaches to the neural investigation of behavioral beliefs [e.g., 45] as, unlike fMRI, it allows for a more unobtrusive capture of the mental processes that occur *during the IS use experience* in a realistic way [83]. While the EEG measurement takes place, the individual is able to use a given technology in a more realistic manner. Second, because EEG is capable of also capturing 'hidden' processes, it provides a more reliable and global picture of evaluative processes during belief formation, thus reducing the inherent biases associated with the exclusive employment of explicit (i.e., perceptual) measures [89]. In sum, the use of EEG together with perceptual measures to assess the formation of behavioral beliefs constructs increases the validity of the results by reducing the likelihood of method biases [81, 83] which represents a critical component of construct and instrument validity in IS research [109, 117, 119].

Practical Implications

This research also has implications for practice. First, our results suggest that memory load is not always detrimental. In fact, when memory load occurs in the absence of frustration it is beneficial for the cognitive evaluation of the technology because adaptation and learning processes are not hampered by negative factors, but rather reinforced by positive feedback leading to positive evaluations of the technology [25, 33]. This suggests that technology does not need to be simple to be perceived as easy to use. In fact, if technology is complex but well designed and provides timely relevant information and features so that the user pursues its task while maintaining low frustration levels, it will be perceived as easy to use. Second, attentional processes also play a beneficial role in the positive evaluation of a technology. Indeed, because engagement includes a pleasurable dimension of the experience with a given technology, it weakens the negative relationship between distraction measures capable of also capturing 'unconscious' distraction states and the perceived usefulness of a technology. On practical grounds, this insight indicates that information or technology features that have the ability to trigger a sustained engagement of the user are likely to produce positive evaluations of the technology.

Limitations and Future Research

As with any research, this study is not free of limitations. For example, the size of the sample, although comparable to accepted sizes for NeuroIS, is small. Thus, future research could be aimed at replicating this study with larger sample sizes. Furthermore, our study only investigated two explicit (perceptual) and two implicit (neurophysiological) antecedents of PU and PEOU. Although the variance explained by these antecedents is high, future research should study other explicit and implicit antecedents of behavioral beliefs, and their interactions. This would complement the explicit and implicit antecedents identified herein. For example, a potentially interesting avenue of future research would be to include the construct of cognitive absorption for longer and/or non directed tasks where users could experience the 'control' dimension of the construct. Finally, and though we made every effort to control for all potential biases inherent to the use of EEG, we believe that future research is needed to more systematically control for potential momentary biases of attention (e.g., fatigue)[8].

Besides the opportunities for future research derived from the limitations of this study, other possibilities for research exist. For example, a second normal step in this domain would be to link the IS artifact with specific implicit and explicit measures of the use experience, in order to provide more specific design guidelines into how to ameliorate the technology use experience, and thus, the overall acceptance of technology. Additionally, future studies could be aimed at investigating not only the interplay of explicit and implicit measures on behavioral beliefs, but also on how these measures contribute to individuals' ability to effectively perform a given computer task. This would shift the focus from acceptance to a more meaningful view of the effective use of technology at work, and provide relevant practical implications. Furthermore, because of the importance of instrument validity in IS research, future research could investigate the temporal correlations of neurophysiological measures and perceptual ones. This would contribute to the IS field by identifying which temporal markers in the use experience matter the

[8] We thank an anonymous reviewer for this insight.

most when users evaluate a given technology. Finally, given the temporal resolution of EEG recordings, research could be aimed at studying users' neurophysiological reactions to technological interruptions or new IS features and their relation to performance in a given task.

Conclusion

After more than thirty years of research on behavioral beliefs and their influence on technology acceptance, we know little about how behavioral beliefs (e.g., perceived usefulness and perceived ease of use) of technology are formed. This study presents a first effort in understanding how implicit (neurophysiological) and explicit (perceptual) states interact during technology use to determine such behavioral beliefs. Fundamentally, our results point to the importance of theorizing and testing for interactions between implicit and explicit measures to get an accurate and more complete picture of how users decide whether a technology is useful and easy to use. Future research can be aimed at replicating this study with a larger sample size, investigating other implicit and explicit antecedents of behavioral beliefs, identifying the implicit and explicit antecedents of effective technology use, testing users' neurophysiological reactions to technological interruptions, and studying the potential temporal correlations between neurophysiological measures and perceptual ones during IS use .

ACKNOWLEDGMENTS

We gratefully acknowledge the helpful and constructive comments of Henri Barki, Fred Davis, Jane Webster, and the review team. We are also indebted to the participants of the Gmunden Retreat on NeuroIS 2012 in Gmunden (Austria) and the Groupe de Recherche en Systèmes d'Information (GReSI) of HEC Montréal for their suggestions and comments. This research was partially funded by a grant from the Social Sciences and Humanities Research Council of Canada (SSHRC) to Ana Ortiz de Guinea, Ryad Titah, and Pierre-Majorique Léger;

by a grant from the Fonds Québécois pour la Recherche sur la Société et la Culture (FQRSC) to Ana Ortiz de Guinea; and by a grant from the Fonds Québécois pour la Recherche sur la Société et la Culture (FQRSC) to Ryad Titah.

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Tables and Figures

Figure 1. The Technology Acceptance Model (TAM)

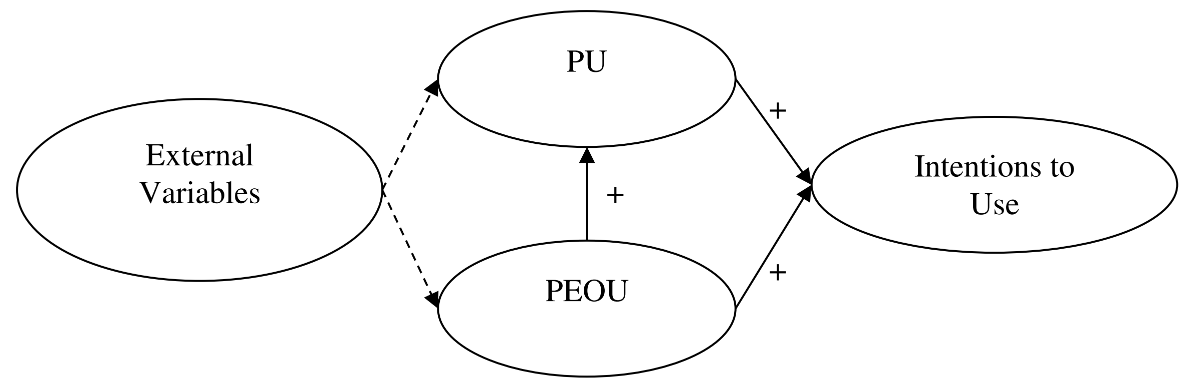

Figure 2. Research Model

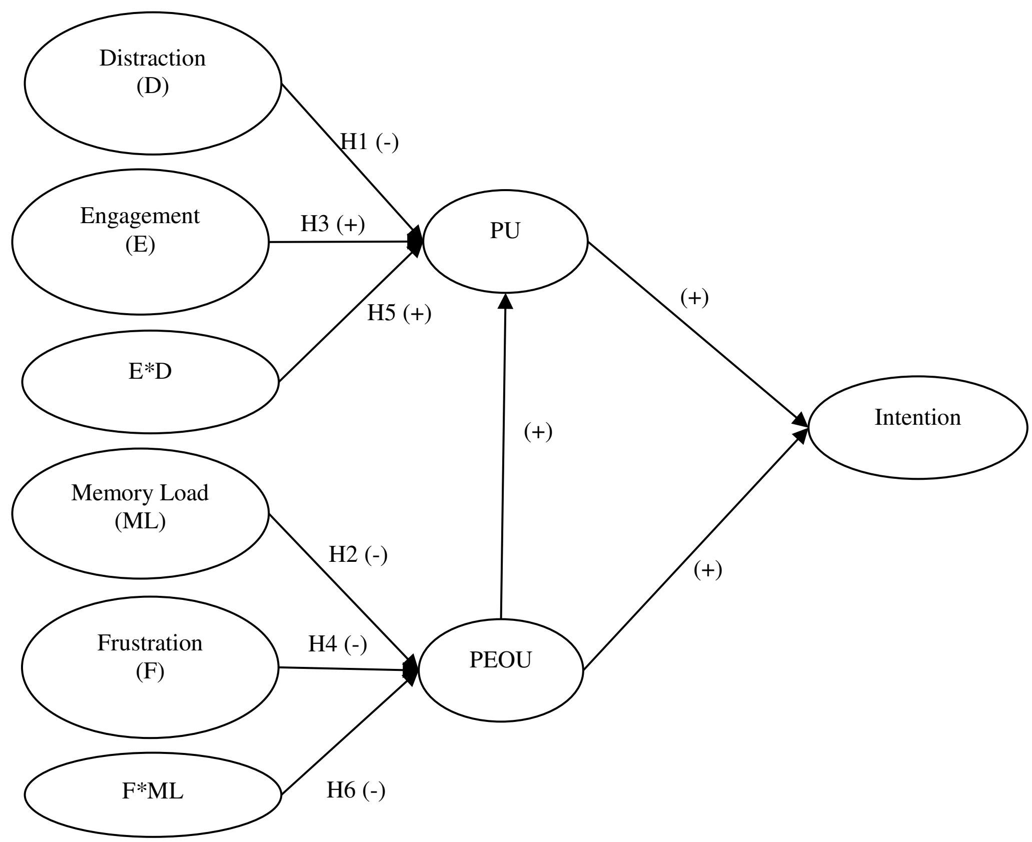

Figure 3. Results: Main Effects

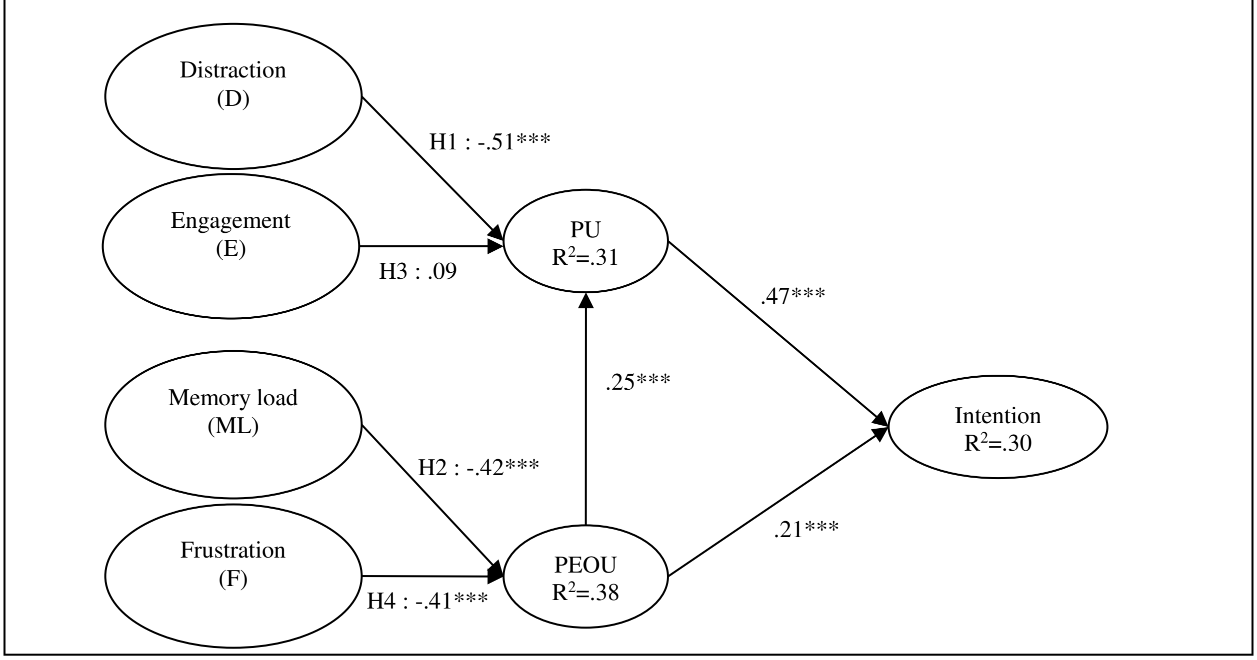

Figure 4. Results: Interaction Effects

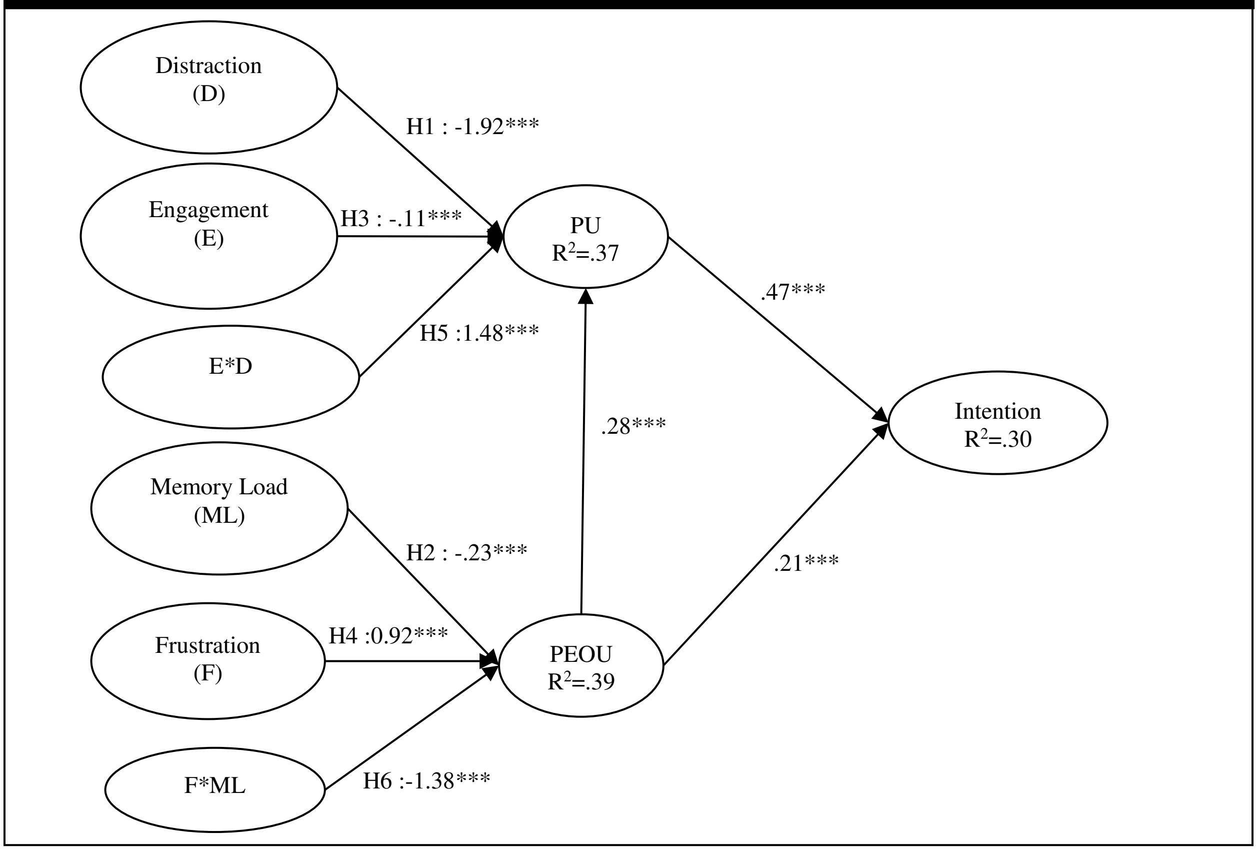

Figure 5. Interaction between Distraction (D) and Engagement (E) on PU

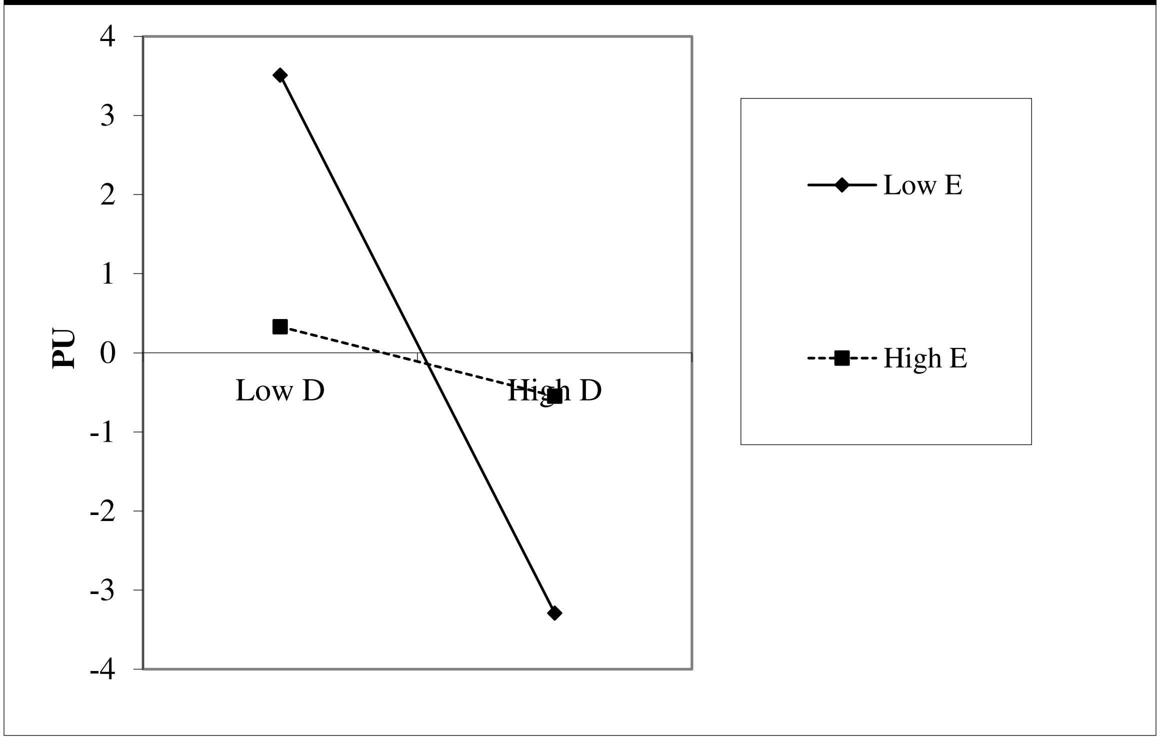

Figure 6. Interaction between Memory Load (ML) and Frustration (F) on PEOU

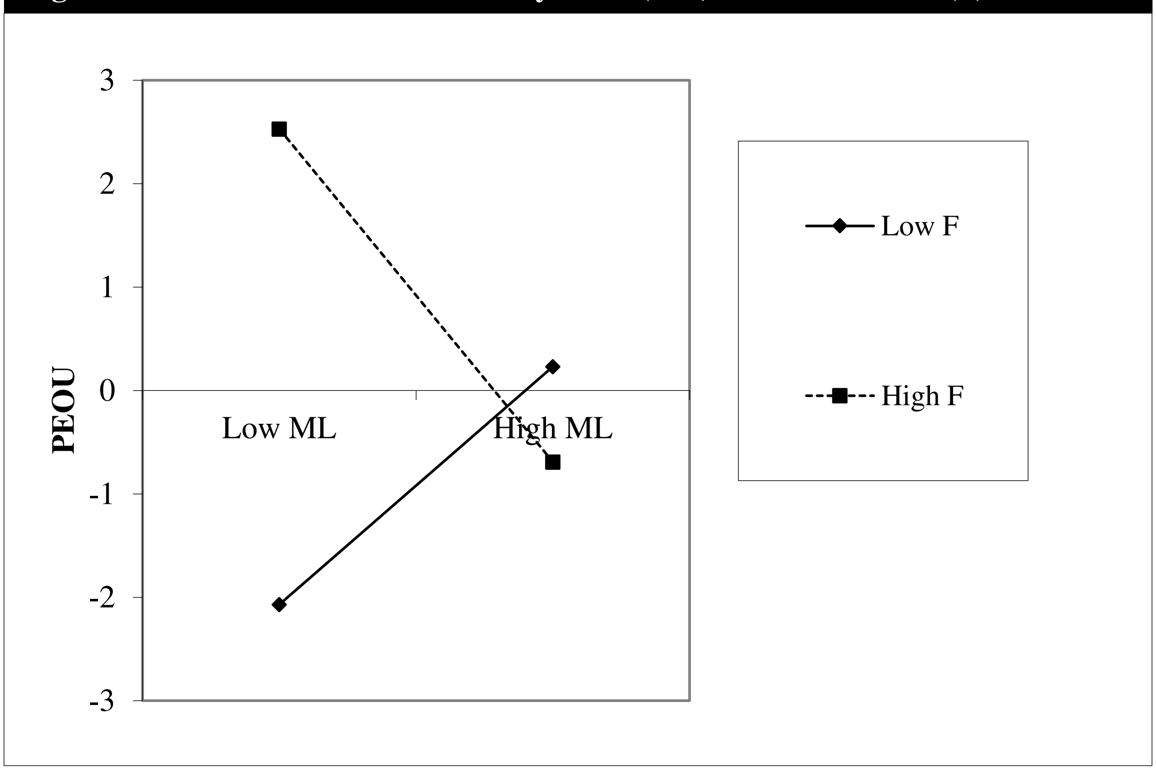

Table 1. Factorial analysis – loadings and cross-loadings							
	I	**PU**	**PEOU**	**E**	**F**	**ML**	**D**
I1	**0.99**	0.51	0.31	0.19	0.03	0.04	-0.12
I2	**0.98**	0.49	0.27	0.18	0.09	0.06	-0.07
PU1	0.54	**0.96**	0.24	0.24	-0.13	0.08	-0.46
PU2	0.42	**0.93**	0.18	0.27	-0.15	0.10	-0.40
PU3	0.45	**0.96**	0.11	0.24	-0.08	0.16	-0.45
PU4	0.51	**0.96**	0.15	0.12	-0.09	0.13	-0.48
PEOU1	0.31	0.23	**0.90**	0.29	-0.40	0.39	0.07
PEOU2	0.29	0.16	**0.95**	0.30	-0.46	0.40	0.20
PEOU3	0.23	0.12	**0.93**	0.17	-0.43	0.46	0.23
E1[1]	-0.13	0.04	0.01	**0.50**	-0.05	0.03	-0.05
E2[1]	0.05	0.11	0.13	**0.58**	-0.11	-0.11	-0.02
E3	0.18	0.18	0.09	**0.85**	-0.09	0.16	-0.19
E4[1]	0.15	-0.05	0.23	**0.55**	-0.09	-0.08	0.01
E5	0.13	0.20	0.47	**0.85**	-0.37	0.21	-0.04
E6	0.27	0.17	0.15	**0.76**	0.01	0.10	0.02
E7	0.03	0.015	0.12	**0.70**	0.08	0.09	0.05
F1	-0.02	-0.30	-0.51	-0.29	**0.86**	0.20	0.05
F2	0.15	0.04	-0.29	-0.08	**0.85**	0.003	-0.10
F3	0.08	0.08	-0.34	-0.06	**0.88**	0.006	-0.12
ML1	0.05	0.12	0.45	-0.06	0.10	**1.00**	-0.19
D1	0.10	0.47	0.18	-0.07	-0.04	-0.19	**1.00**

[1]**Note:** Though the internal validity of the engagement scale has been demonstrated in past research [133, 134] we decided to drop items E1, E2 and E4 from the study because their loadings were below the recommended threshold of .6 [53].

Table 2. Correlation Matrix, Reliabilities, VIFs and square root of AVE (shown in the diagonal)										
	Composite Reliabilities	**VIF**	**Mean (St.Dev.)**	**I**	**PU**	**PEOU**	**E**	**D**	**F**	**ML**
I	.98		5.54 (.05)	.97						
PU	.98	1.04	4.29 (.08)	0.50	.95					
PEOU	.95	1.04	5.65 (.02)	0.29	0.18	.93				
E	.86	1.10	5.32 (.57)	0.18	0.22	0.27	.69			
D	N/A	1.14	N/A	-0.01	-0.47	0.18	-0.08	1.00		
F	.90	1.01	2.15 (.12)	0.06	-0.11	-0.46	-0.19	-0.04	.87	
ML	N/A	1.01	N/A	0.05	0.12	-0.45	-0.07	-0.19	0.10	1.00

Table 3. Effect of D on PU at different levels of Engagement (based on Figure 5)			
E	**Coef. D**	**Standard Error**	**t-value**
7	0.50	1.89	0.26
6	-0.98	1.62	-0.61
5.32 (mean of E)	-1.99	1.44	-1.38
5	-2.46	1.36	-1.81
4	-3.94	1.10	-3.58***
3	-5.42	0.85	-6.41***
2	-6.90	0.60	-11.49***
1	-8.38	0.38	-21.80***
0	-9.86	0.28	-35.55***

Table 4. Effect of ML on PEOU at different levels of Frustration (based on Figure 6)			
F	**Coef. ML**	**Standard Error**	**t-value**
7	-6.92	3.13	-2.21***
6	-5.54	2.68	-2.07***
5	-4.16	2.24	-1.86
4	-2.78	1.79	-1.55
3	-1.40	1.35	-1.04
2.12 (mean of F)	-0.23	0.97	-0.24
2	-0.02	0.91	-0.03
1	1.36	0.48	2.86***
0	2.74	0.16	16.60***

Table 5. Effect Sizes		
	Effect size f^2	**Classification of Effect Sizes[a]**
Model with main effects (without interaction effects)		
Effect size of D on PU	0.36	Large
Effect size of E on PU	0.07	Small
Effect size of ML on PEOU	0.26	Medium
Effect size of F on PEOU	0.28	Medium
Model with interaction effects		
Effect size of D*E on PU	0.10	Small
Effect size of ML*F on PEOU	0.02	Small
[a]Note: Cohen (1988) classifies effect sizes as follows: .35 as large, .15 as medium, and .02 as small.		

Appendix: Explicit (Self-Reported) Measures

Measures	Scale	Source
Frustration: While using the system: - (F1) Trying to get this task done was a very frustrating experience - (F2) Being frustrated comes with this task - (F3) Overall, I experienced a lot of frustration on this task	I disagree/ I agree 7-point scale	Peters et al. [88]
Engagement: While using the system, the task: - (E1)[1] Kept me totally absorbed in the browsing - (E2)[1] Held my attention - (E3) Excited my curiosity - (E4)[1] Aroused my imagination - (E5) Was fun - (E6) Was intrinsically interesting - (E7) Was engaging	I disagree/ I agree 7-point scale	Webster et al. [135]
PU: - (PU1) Using the system improves my performance in my task. - (PU2) Using the system in my task increases my productivity. - (PU3) Using the system enhances my effectiveness in performing my task. - (PU3) I find the system to be useful to performing my task.	I disagree/ I agree 7-point scale	Venkatesh and Davis [130]
PEOU: - (PEOU1) My interaction with the system is clear and understandable. - (PEOU2) I find the system to be easy to use. - (PEOU3) I find it easy to get the system to do what I want it to do.	I disagree/ I agree 7-point scale	Venkatesh and Davis [130]
Intention: - (I1) Assuming I had access to the system, I intend to use it. - (I2) Assuming I had access to the system, I predict that I would use it.	I disagree/ I agree 7-point scale	Venkatesh and Davis [130]
[1]**Note:** Though the internal validity of the engagement scale has been demonstrated in past research [133, 134] we decided to drop items E1, E2 and E4 from the study because their loadings were below the recommended threshold of .6 [53].		