
**Neurophysiological Correlates of Cognitive Absorption in an Enactive Training Context**

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Abstract

Various aspects of intrinsic motivation have long been theorized as key determinants of learning achievement. The present research seeks deeper insights into these intrinsically motivating mechanisms by investigating neurophysiological correlates of cognitive absorption in the context of enactive learning, specifically simulation-based training on the use of enterprise resource planning (ERP) software. An experiment was conducted in which 36 student trainees used ERP software to make decisions while running a simulated company. Consistent with flow theory, skill, difficulty, and their interaction significantly influenced cognitive absorption ($R^2 = .16$). Five neurophysiological measures were captured for each trainee: EEG alpha, EEG beta, electrodermal activity (EDA), heart rate, and heart rate variability. Each of the five neurophysiological measures explained significant unique variance in cognitive absorption over and above skill, difficulty, and their interaction, and collectively more than doubled the explained variance to $R^2 = .34$. Overall, cognitive absorption was positively related to a more relaxed, less vigilant state. Cognitive absorption was significantly related to the training outcome. These findings provide new insights into the psychological states that are conducive to experiencing cognitive absorption during enactive training.

Highlights:

- Neurophysiological variables doubled the explained variance
- Based on EEG data, we find that cognitive absorption is positively related to a more relaxed (increased EEG Alpha), less vigilant state (decreased EEG Beta).
- Perceived control appears to have the strongest effect on training outcome

Keywords: NeuroIS, neurophysiological measures, end-user training, cognitive absorption, enactive learning
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1. Introduction

End-user training has long been recognized as a key factor in the acceptance and effective use of information technology (IT) (Compeau & Higgins, 1995; Nelson & Cheney, 1987). The objective of end-user training is to produce a skilled user who is motivated to apply this newly acquired knowledge in order to perform a job-related task (Gupta et al., 2010). Moreover, organizations are investing significant resources in end-user training. According to the US Bureau of Labor Statistics, every year over 170 Billion US$ is spent on employee training and development; the American Society for Training and Development (ASTD, 2011) estimates that IT training accounts for 10% (on average) of all formal learning hours over the past ten years. Research shows that poor or insufficient training results in limited acceptance of the technology, which prevents organizations from fully realizing the benefits from these significant new investments (Compeau & Higgins, 1995; Nelson & Cheney, 1987). For example, undertrained end-users could cost five to eight times more to support than a well-trained worker (Fiering & Kirwin, 2006).

Among the various techniques used to train IT users, researchers call for more enactive methods (De Freitas & Jarvis, 2007; Derouin et al., 2005; Hays, 2005; Hedberg, 2003; Kirkle et al., 2005; Mayo et al., 2006). Enactive learning is based on social cognitive theory (Bandura, 1986) and is a form of observational learning that involves learning as a consequence of one’s interaction with and feedback from the environment. Gupta (2010) provides evidence that combining enacting learning with vicarious learning (learning by observing others) leads to better training outcomes compared to vicarious learning alone. Realistic simulations provide a training context that generates relevant feedback in response to learner actions. More research is needed to properly understand such enactive learning in IT training (Martocchio & Webster, 1992; Sein et al., 1999). Computer-based simulation games have been
demonstrated to be more effective than alternative forms of training for teaching work-related knowledge and skills (Sitzmann, 2011). Moreover, computer-based simulation games more readily incorporate enactive learning (as opposed to learners simply observing others). Consequently, the advantages of computer-based simulation training are theorized to result primarily from intrinsic motivation experienced by trainees when they actively engage in learning the training material (Sitzmann, 2011). Léger et al. (2012) report that learning is perceived to occur more so during the enactive period (such as during a simulation of an IT training) as compared to other more direct instruction periods (such as a more formal presentation). While the literature provides evidence of the effects of affective and cognitive states on training outcomes, further investigation is needed on the impact of such psychological states on training effectiveness in enactive learning contexts (Gupta et al., 2010).

The present research focuses on the relationships between neurophysiological measures and the cognitive and affective states related to effective enactive IT training. The purpose of the paper is to determine the relationships, if any, that exist between neurophysiological measures and cognitive absorption (CA). Specifically, the paper focuses on the relationships between individuals’ cognitive absorption (and its dimensions) and EEG (electroencephalography), EKG (electrocardiography), EDA (electrodermal activity) and HR (Heart rate). Understanding these relationships could further enhance end-user and IT training as well as user acceptance of technology and systems. Moreover, the results of such studies not only contribute to the current call for research on end-user training, but also point to the importance of considering neurophysiological factors along with trainees’ experience and task difficulty when developing effective IT training. Enactive training programs can perhaps be designed to induce neurophysiological states that will result in more efficient and better use of the technology. Such insights could open up new frontiers for advancing the development of more efficient, effective, and enjoyable training environments; and hence, enhanced user acceptance and efficient use of technology. Given the continuing high failure rate of new information systems implementations, much of which can be directly attributed to inadequate training practices, the quest for such insights warrants urgent attention.
2. Cognitive Absorption

Based on flow theory (Csikszentmihalyi, 1990), cognitive absorption is conceptualized as a state of deep involvement with IT (Agarwal & Karahanna, 2000). Research suggests that cognitive absorption significantly affects trainees’ behavioral intention to use the target information system both directly and through its indirect effects via perceived usefulness and perceived ease of use (Agarwal & Karahanna, 2000; Saadé & Bahli, 2005; Scott & Walczak, 2009; Shang et al., 2005). Stated differently, training that can enhance cognitive absorption is of high interest because it is theorized to lead to better training outcomes and, in turn, enhanced acceptance and more effective use of information systems. Neuroscience provides insights into how brain activity changes during the acquisition of a new skill or competence (Hill & Schneider, 2006). Initial skill acquisition places great demands on domain-general control circuitry generally located in the prefrontal cortex (Chein & Schneider, 2012). As a learner becomes more effective at a task, activity in the prefrontal areas of the brain reduces significantly (specifically in regions related to task control and working memory). As a new cognitive skill is acquired, one evolves from a state of controlled processing of stimuli to more automatic and effortless processing involving subcortical circuitry.

A cognitively absorbed IT user is intrinsically motivated and in a state of deep attention that consumes all of this individual’s resources (Saadé & Bahli, 2005; Shang et al., 2005). CA has been conceptualized by Agarwal et al. (2000) as a multi-dimensional construct with five dimensions -- temporal dissociation (the inability to register the passage of time while engaged in interaction), focused immersion (the experience of total engagement where other attentional demands are ignored), heightened enjoyment (the pleasurable aspects of the interaction), control (the user’s perception of being in charge of the interaction), and curiosity (the extent to which the experience arouses an individual’s sensory and cognitive curiosity). There is longstanding theory and research linking various aspects of intrinsic
motivation and cognitive absorption in learning achievement context (Ryan & Deci, 2000; Skinner, 1996), but also in other contexts such as online shopping and social media.

CA is theoretically rooted within the concepts of absorption (Tellegen & Atkinson, 1974), cognitive engagement (Webster & Ho, 1997), and flow (Csikszentmihalyi, 1990). According to flow theory (Csikszentmihalyi, 1990), individuals experiencing this state are so intensely concentrated on the event that they lose track of time, and feel in total control of the situation. It is also theorized that in such as state, “people are willing to do an activity for its own sake, with little concern for what they get out of it” (Csikszentmihalyi, 1990: 71). The balance between the challenge of a task and the skills required to execute this task is generally seen as a key antecedent to the emergence of a flow state (Csikszentmihalyi, 1990). When the level of difficulty under a specific task matches the skills, the individual is then able to perceive being in control of the task at hand, and can devote all their attention to its realization. The task must present sufficient challenges so that the resources of the individual are fully dedicated to its realization. In contrast, when the difficulty outmatches the skill, the individual is likely to be too anxious to achieve a flow state. Similarly, if the difficulty is too low for the given skill, the individual is likely to be bored. For an application of this concept in the context of sports, see Ellis & Voelkl (1994).

Rani et al. (2005) report the self-perceived psychological state of players in video games under various difficulties. Their results show that, when a player perceives that the difficulty is too low, subjects seem to be bored, and when the difficulty is too high, subjects are perceived as being anxious. Subjects who were reported being in a state of flow were neither bored nor anxious. Nacke and Lindley (2008) show that, when there is a linear progression of difficulty, players are more likely to build their skills, and over time achieve a self-reported state of flow. They also find that when players are faced with an initial difficulty which surpasses their skill level, the anxiety of the player makes it very unlikely to achieve a state of flow. Drachen et al (2009) find similar evidence by manipulating the level of skills within a gaming context under various levels of difficulty; their results support the emergence of the various states of mind described by Ellis and Voelkl (1994) when skills and challenge are not balanced.
3. Neurophysiological Correlates of Cognitive Absorption

Hanin (2000) proposes a framework to capture the psychological and physiological states of the flow state for an individual task. Their model suggests that the overall psychophysiological disposition of an individual is also an important factor in being able to achieve a state of flow. In this framework, the psychological dimension refers to the affective, cognitive, and motivational components; while the physiological dimensions consist of behavioral and bodily-somatic factors. According to Hanin (2000), both psychological and physiological dimensions are essential to understand cognitive and emotional conditions underlying a flow state. Peifer (2012) proposes an integrative definition of flow experience which states that flow is a positive valence state (affective component), resulting from an activity that has been appraised as an optimal challenge (cognitive component), characterized by optimized physiological activation (physiological component) for full concentration on coping with environmental/task demands (behavioral). Recent research in the IT literature has proposed to enrich current flow measures by capturing implicit (i.e., automatic and unconscious) psychophysiological measures in conjunction with more explicit (i.e., self-report) measures of flow (Ortiz De Guinea et al., 2013). Specifically, Ortiz de Guinea et al. (2013) have shown that a) measures of flow states captured only by self-report appear to suffer from mono-method biases, and that b) because of the retrospective nature of self-report measures, they show only moderate correlations (between 0.37 and 0.58) with psychophysiological measures that capture flow during the whole experience.

Neuroscience research provides empirical evidence of how brain activity changes during the acquisition of a new skill or competence can help to understand these cognitive and emotional conditions (Hill & Schneider, 2006). In the early stages of learning a new skill, the learner must exert a significant amount of cognitive energy to handle the processing of stimuli in order to perform the target task. This controlled processing involves intense cognitive activity in the brain regions related to task control and working memory (especially the DLPFC). As a new cognitive skill is acquired, one evolves from a state
of controlled processing of stimuli to an automatic and effortless processing state. As a learner becomes more effective at a task, the activity in the prefrontal areas of the brain reduces significantly (Hill & Schneider, 2006).

Given an understanding of flow theory and how brain activity changes during the acquisition and performance of skills, we generally hypothesize the existence of the relationships between neurophysiological measures and cognitive absorption:

\[ H1: \text{ There is a relationship between the neurophysiological state of the IT learner and his/her perception of being cognitive absorbed. } \]

There is a growing literature using psychophysiological signals to infer individual flow experiences. Flow states appear to be associated with several psychophysiological responses that can be captured using unobtrusive neurophysiological measurement devices (Peifer, 2012). The following sections hypothesize the relationship between various neurophysiological signals and the concept of cognitive absorption.

3.1 Electroencephalography (EEG)

EEG measures the electrical activity of the brain. It reflects postsynaptic potential of the neuronal activity resulting from ionic current flows within the neurons of the brain. EEG records the difference of potential between an active electrode placed on various areas of the scalp and a passive electrode (on the ear lobe, for example). Most of the signal power is under 100 microvolts and is attributable to oscillation under 30 Hz, specifically the delta band (1-4 Hz), theta band (4-7 Hz), alpha band (8-12 Hz) and beta band (13-30 Hz).

In general, EEG alpha activity is thought to be related to attentional demands whereas beta activity is related to emotional and cognitive processes (Ray & Cole, 1985). Research suggests that increases in beta activity are associated with a higher level of vigilance in a task and is a marker of hypervigilance (Freeman et al., 1999). As an individual becomes calmer, more relaxed and less vigilant
during a task, the power of the EEG signal changes significantly: the alpha band increases while the beta band decreases (Berka et al., 2007; Davidson et al., 1990; Freeman et al., 1999; Prinzel et al., 2000; Ray, 1990). Higher beta power has been found to be associated with personal distress (Woodruff et al., 2011). In contrast, van Boxtel et al (2012) explain that alpha is associated with relaxed wakefulness and subjective feelings of relaxation, well-being, and reduced anxiety. Alpha is associated with top-down attention control processes related to the activation of the central executive component of working memory (Klimesch et al., 2007) and the inhibition of distracting information (Freunberger et al., 2011). Alpha power appears to support the coordination of internal mental processes (Hanslmayra et al., 2011; Knyazev et al., 2011).

In the flow state, an individual uses highly practiced skills without the interference of analytical and meta-cognitive capacities, therefore requiring less activity in the prefrontal areas of the brain which are associated with higher cognitive function (Dietrich, 2004). Using electroencephalography, Hamilton et al. (1984) found a negative relationship between mental effort and high intrinsic enjoyment contexts. Similarly, Nacke (2009) show that immersion in a gaming environment elicits less activity in the theta band (4-8 hz), which is generally associated with a decrease in mental workload.

Flow theory posits that, when the level of difficulty under a specific task matches the skills, the individual enters an intrinsically motivated state of dedicated attention (without being hypervigilant and overly anxious). In other words, one should be awake, calm, and in a relaxed state, with a feeling of well-being and control. This implies a lower level of beta activity and a higher level of alpha activity. Based on evidence from neurophysiological research, we pose the following hypothesis regarding EEG:

\( H1A: \) There is a positive relationship between EEG alpha and the perception of being cognitively absorbed

\( H1B: \) There is a negative relationship between EEG beta and the perception of being cognitively absorbed.
3.2 Electrodermal activity (EDA)

Other non-obtrusive methods such as electrodermal activity (i.e., electrical changes measured at the surface of the skin), which reflect the arousal of an individual, have also been reported to be associated with the flow state. Electrodermal activity (EDA) (also called galvanic skin response or skin conductance) refers to the production of sweat in the eccrine sweat glands, which is entirely controlled by the human sympathetic nervous system (Boucsein, 1992). EDA is an index of autonomic nervous system activity measured by the potential difference between two areas of the skin (Dawson et al., 2007). Increased sweat gland activity is related to electrical skin conductance. EDA has been widely used as an objective measure of emotional arousal (Bradley et al., 1993; Lang, 1995). EDA is also reported to be associated with the flow state (Mandryk & Atkins, 2007).

In a flow condition, individuals experience an optimal level of stress that Hancock and Warm (1989) refer to as a psychological zone of maximal adaptation, or comfort zone. When the flow conditions are not meet, the individual becomes bored (hypostressed) or very anxious (hyperstressed). In sum, the more aroused a person, the less they are calm and focused and in control of the task.

In this paper, we posit that an individual who is cognitively absorbed is more likely to be emotionally stable, thus exhibit less spontaneous electrodermal response. This is generally refered as non specific electrodermal response (NS.EDR). Besthorn et al (1989) suggest the use of the standard deviation of the NS.EDR amplitude to capture the variance of over audio-visual stimulation lasting from 1.5 to 3 minutes. This measure has also been recently used in an IS context to measure the emotional response of ERP users (Léger et al., Forthcoming). A person with an optimal flow state is neither bored nor anxious. They are in an optimal state that balances between the challenge of a task and the skills required for the task. They are not too anxious, nor are they too vigilant. This individual maintains a deep level of attention and is concentrating intensely. On one hand, if the challenge becomes too intense for a given level of skill required, the person will become anxious which is likely to increase the variation of NS.EDR. On the other hand, if the task is too easy for the level of skill required, the person will become
bored which is likely to lead to the variation of NS.EDR. We argue that a learner in an optimal flow condition will have a smaller variance in EDA because of the nature of this balance state, therefore:

\[ H1C: \] There is a negative relationship between the variation of non specific skin conductance response and the perception of being cognitively absorbed.

3.3 Heart rate (HR) and Heart Rate Variability (HRV)

Previous studies have associated heart rate variability with cognitive dimensions of the flow state associated with an optimal challenge. For example, cardiovascular measures have been used to infer the mental load, which can be used to identify flow states (de Manzano et al., 2010; Keller et al., 2011). We also posit that a cognitively absorbed individual is likely to require less mental effort to perform their task. In a flow condition, individuals experience an optimal level of cognitive effort when using the software. When the cognitive effort is too high, flow conditions are difficult to maintain and the individual is likely to perceive lower level of cognitive absorption. Cardiovascular measures can also characterize the neurophysiological state of an IT learner. Heart rate (HR) corresponds to 60000 divided by the time in msec between adjacent heart beats while heart rate variability (HRV) refers to the variance among heart rates in a time period. The autonomic nervous system (ANS) activity is divided into two branches: sympathetic and parasympathetic, controlled by the Nucleus of Tractus Solitarius (NTS), thereby modulating heart rate (Cacioppo et al., 2007). Sympathetic activity is primarily related to the preparation of the body for action as well as stressful situations. Alternatively, parasympathetic activity, active under restful situations, counterbalances the effects of the sympathetic activity in order to restore the body to a resting state (also called homeostasis). Under normal situations, there is a balance between these two activities (Kumar et al., 1996).

Effort influences the autonomic nervous system, and therefore affects the cardiovascular measures, such as HR and HRV (Veltman & Gaillard, 1998). Several studies in the field of neuroergonomics provide evidence of a relationship between both HR and HRV and cognitive effort; HR
increases with an increase in cognitive effort (and HRV decreases with an increase in cognitive effort (Jorna, 1992; Roscoe, 1992; Wilson, 2001, 2002)). For example, many studies in aeronautics demonstrate the effect of a momentary change in mental effort on the cardiovascular system both for pilots (e.g. (De Rivecourt et al., 2008)) and air traffic controllers (Brookings et al., 1996). In addition, HR and HRV have been shown to be sensitive to task difficulty levels when operating an aircraft (Boer & Veltman, 1997; Roscoe, 1975; Roscoe, 1993; Veltman & Gaillard, 1998). Moreover, Scerbo, Freeman, Mikulka, Parasuraman, et al. (2001) indicated that cardiovascular measures (such as HR and HRV) provide the strongest correlates of workload. Therefore, we pose the following regarding HR and HRV.

H1D: There is a negative relationship between HR and the perception of being cognitively absorbed.

H1E: There is a positive relationship between HRV and the perception of being cognitively absorbed.

3.4 Cognitive Absorption and Learning Outcomes

In this paper, we argue that, in a training context, greater cognitive absorption will result in a better training outcome. Flow theory claims that people under flow condition, due to the intrinsically rewarding experience, will try to achieve “higher levels of performance” (Csikszentmihalyi, 1990) (p.74) and are likely to perceived their performance to be pleasurable and successful (Nakamura & Csikszentmihalyi, 2002). This attitude pushes them to explore and to repeat this experience, which contribute to learning and optimal performance Trevino and Webster (). The impact of the flow state has been tested in several contexts. For example, the state of flow has been involved in understanding peaking performance in sports (Jackson & Roberts, 1992) and job performance (Demerouti, 2006). In the context of education, flow state increases the likelihood of school completion (Christenson et al., 2001) and overall performance in college (Shernoff & Hoogstra, 2001). Also, evidence suggests that flow has a positive effect on outcomes in a gamified training environment (Admiraal et al., 2011). We thus pose the following hypothesis.
H2: There is a positive relationship between being cognitively absorbed and the training outcome.

Figure 1 summaries our research model and displays our research hypothesis.

*** Insert Figure 1 Here***

4. Methodology

4.1 Experimental Protocol

An experimental approach was used to test these hypotheses. Thirty six (36) right-handed male and female subjects took part in a two-hour simulation-based training session on an ERP system. The experiment was approved by the Institutional Review Boards (IRB) of the institutions involved in the study. The IRB reviews research protocols and procedures to ensure the appropriateness of the study. All subjects were undergraduate students from an AACSB accredited institution, in the United States, and almost half of the subjects had never used this ERP system before.

To incorporate enactive learning, the research methodology involved the use of simulation software called ERPsim (Cronan et al., 2012; Léger, 2006; Léger et al., 2011; Léger et al., 2012; Léger et al., 2007). In the training environment ERPsim is designed to recreate a realistic business context in which trainees manage the main business processes within an organization using the ERP system (i.e. SAP). Recent research results provide support for the authentic nature of this enactive ERP simulation (Léger et al., 2012). In the context of this study, participants were playing alone against a computerized opponent.

During the simulation, participants had to make critical business decisions, and proactively manage the day-to-day operations of their company while competing against other companies operating in the same market. Before playing the simulation game, subjects confirmed voluntary participation by signing a consent form. Next, they were provided standardized instructions on the experimental procedure. Subjects first answered a pre-survey to measure the pre-existing skill of the participants and then watched a training video on the ERP system (20 minutes). After each game, participants answered a
cognitive absorption survey. As compensation, subjects received a $25 US gift card from Amazon and they also received lottery ticket to win a prize valued at about 100$ (i.e. Apple TV) based on their performance (i.e. training outcome) in the game to heighten competitiveness among players.

The study was conducted over a two week period to limit the impact of outside temperature variation on the subject electrodermal activity. The experimental room temperature and humidity was kept constant during the duration of the experiment.

4.2 Operationalization of the variables

To manipulate the difficulty of the task, three (3) versions of the simulation game were used: easy, medium, and hard. To create a within-subject manipulation, all subjects played two (2) simulations that differed in terms of complexity. The subjects were randomly assigned to two of the three game versions, with order of presentation randomized to counterbalance.

Skill was measured using an objective survey developed by Cronan et al (2012) before the experiment. This survey include 15 questions developed by the researcher to cover the three dimensions of ERP knowledge (business process knowledge, transactional knowledge and knowledge about enterprise system in general) as defined by (Cronan et al., 2011). Skill thus corresponds to the percentage of valid answers out of the 15 questions.

Cognitive Absorption (CA) was measured using Likert scale of 15 items adapted from (Barki et al., 2008) covering the 5 dimensions of the construct (see table 1). Each dimension exhibits the appropriate level of reliability based on Cronbach’s alpha (one item for control was dropped because of low correlations).

*** Insert Table 1 here ****

Training outcome measures the profit generated by the participant during the simulation. Profit viewed in this context is a proxy of the subject’s ability to apply his skill in order to solve the business
problem given the level of difficulty. To allow inter-subject comparison, profit was standardized to have a mean of zero and a standard deviation of one for each version of the simulation game (easy, medium and hard). Subjects were informed of their profit after answering the cognitive absorption survey to eliminate the endogenous effect.

4.3 Neurophysiological montage, data acquisition and processing

Upon signed consent, pre gel Ag/AgCl electrodes were placed on each subject’s left palm to measures their electrodermal activity (EDA). An electroencephalographic (EEG) sensor was also placed on scalp location F3; this position was chosen because it is one of the nearest to the dorsolateral prefrontal contex (DLPFC) which is related to task control and short-term memory (Fitzgerald et al., 2009). EEG references were placed on the ear lobes. Heart rate data were collected from sensors placed over the sternum and the seventh intercostal space on the left and right side of the chest. Neurophysiological measures were gathered using the Procomp Infinity encoder from Thought Technology. EDA was collected at 32 HZ from using a Thought Technology SC sensor - Flex/Pro SA9309M. EEG was acquired from F3 at 2048 Hz using a Thought Technology EEG sensor - Z SA9305Z. HR was collected with a Thought Technology EKG sensor - Flex/Pro T9306M. A waiting time was applied after attaching the electrode for optimal data acquisition with gel electrodes.

Three minutes of artifact-free EDA, HR, HRV, & EEG data prior to the two cognitive absorption surveys were used for data processing and analysis. The standard deviation of non-specific electrodermal response (EDR) was deartefacted and normalized EDA using Matlab (signal processing and curve fitting toolboxes) based on Mandryk et al (2007) and (Besthorn et al., 1989). HR corresponds to 60000 divided by the time in msec between two adjacent heart beats (Cacioppo et al, 2007). HRV is measured using a time domain metric called SDNN, which corresponds to the standard deviation of the normal beat to normal beat interval (Cacioppo et al, 2007). We derived SDNN over the 3 minutes periods before the cognitive absorption survey. EEG data were de-artifacted and manually inspected with the Matlab toolbox EEGlab Also, Matlab was used to calculate the power spectrum analysis of the signal, especially by using
a 3 minutes Hanning window and a Fast Fourier Transform (FFT) analysis as recommended by (Freeman et al., 1999; Freeman et al., 2004). The power spectrum of the alpha band was obtained by summing the power of frequencies ranging from 8 to 12 Hz (EEG Alpha) and from 12 to 22 Hz for the beta band (EEG Beta).

4.4 Research Models

Model estimation used a repeated measure data set from 36 subjects played 2 simulations, thus answering twice the cognitive absorption survey. However, five (5) observations were lost due to problems with neurophysiological data acquisition, leading to 67 valid observations. Stata 12 software was used to perform the regression analysis. Due to the non-independent nature of the observations (2 consecutive observations by subject) and our small sample size, a within-subject correlations technique was applied. Specifically, a well established regression procedure called “option cluster ID” in the Stata regression procedure was used. The cluster option ID corrects for within-subject correlations in order to take into account non-independence by estimating the model by OLS while using the Huber-White (robust) estimates of variance (Crott & Briggs, 2010). Stated differently, we clustered the standard errors at the subject level to correct for within subject correlations as in (Siegel & Larson, 2009). Theoretical and simulation research support this procedure as a conservative and reliable method within a small sample context by (Stock & Watson, 2006). Further information about this procedure can be found in (StataCorp., 2007) (p. 1691).

5. Results

This research presents evidence of links between specific neurophysiological markers of controlled and automatic processing, and user trainees’ perceptions of cognitive absorption. EEG (electroencephalography), EDR (electrodermal activity) and HR (Heart rate) data were gathered using the Procomp Infinity encoder from Thought Technology. Descriptive statistics and correlations are presented in Table 2.
Table 3 compares the effects of two different models on the comprehensive cognitive absorption construct: i) a model that only includes difficulty, skill and their interaction and ii) a model that also includes the psychophysiological variables. As shown in Table 3, the overall results indicate that significant relationships exist between all neurophysiological markers of cognitive and emotional states, and the cognitive absorption of the IT learner. The results indicate that neurophysiological markers explain a substantial amount of the variance in cognitive absorption above and beyond that accounted from by skills and difficulty alone. Specifically, adding measures of different EEG waves (alpha and beta), HR, HRV and EDR increased the amount of variance explained from 16% (skills and difficulty alone) to 34% for the comprehensive CA construct. The results indicate that cognitive absorption is positively related to a more relaxed, less vigilant state of the learner (after controlling for the the difficulty of the task and trainees’ beginning level of expertise).

The size and direction of the effect on neurophysiological markers all correspond to the hypotheses (β and p values are reported in Table 3). The results indicate a relationship between both EEG alpha and CA (β = 2.73, p < 0.05), and the relationship between EEG beta and CA (β = -17.28, p < 0.05); thus, hypotheses 1A and 1B are supported. Subjects with high EEG alpha and low EEG beta (individuals who were calmer, more relaxed, and less vigilant during a task) reported being more cognitively absorbed than others. In addition, participants that exhibited smaller variation of EDR (more emotionally stable with an optimal level of stress) were more likely to be in a cognitively absorbed state (β = -6.42, p < 0.05). Thus, hypothesis 1C is supported. Finally, subjects with lower HR (β = -0.04 , p < 0.05) and higher HRV (β = 0.05 p < 0.05), i.e. individuals experiencing a lower level of cognitive effort when using the software as measure by the cardiovascular system, reported a higher level of cognitive absorption than others. Thus, hypotheses 1D and 1E are supported.
Table 4 presents results with skills and difficulty included in addition to the neurophysiological markers when the individual dimensions of the CA constructs are the dependent variables. To help the comparison, the effect on the comprehensive CA construct was also included in the table. It should be noted that the effects on neurophysiological markers are stronger for some underlying dimensions of the cognitive absorption. The perceived control (CA_CO) and focused immersion (CO_FI) dimensions are constructs for which the model provides the highest explained variance (R²). The explained variance for CA_CO increases from 21.1% to 48.9% when adding the neurophysiological markers. For the CO_FI dimension, explained variance increases from 14.0% to 31.0% with the neurophysiological markers added. For the CO_CU dimension, while the variance explained is lower, 18.3%, the increase due to the neurophysiological marker is 14.1%. The dimensions temporal dissociation (R² = 21.2%) and heightened enjoyment (R² = 17.8) exhibit somewhat lower delta R² values with an increase in R² of 6.75% and 6.80%, respectively.

*** Insert table 4 here ***

Table 5 presents a summary of the significant effects of all five neurophysiological markers on CA and individually on the five CA dimensions. While the effects on the higher level constructs are consistent with our research expectations, it is interesting to note that the neurophysiological markers do not appear to have the same effect on all dimensions. EEG Alpha seems to only have a significant positive effect on perceived control (β = 5.57 p < 0.001). EEG Beta appears to have an effect on more dimensions; it negatively impacts perceived control (β = -34.59 p < 0.001), temporal dissociation (β = -22.08, p < 0.05) and focused immersion (β = -17.78, p < 0.05). EDR appears to only negatively influence the perception of control (β = -10.49, p < 0.01) and focused immersion (β = -8.63, p < 0.05). Finally, the cardiovascular markers appear to also significantly influence focused immersion (HR β = -0.06, p < 0.05; HRV β = 0.05, p < 0.05), but they also have a unique effect on the two other dimensions of cognitive absorption, curiosity (HR β = -0.07, p < 0.05; HRV β = 0.05, p < 0.05), and heightened enjoyment (HRV
\[ \beta = 0.07, \, p < 0.05 \]. Taken together, it appears that the dimensions of the cognitive absorption construct are not influenced by the same neurophysiological markers.

*** Insert Table 5 ***

Table 6 presents the results of model 5 testing the effect of cognitive absorption on training outcome (hypothesis 2). To control for the indirect effects of difficulty, skill, and five of the neurophysiological variables, we included these covariates in the regression model; only the significant variables (i.e. HR and HRV) are included in the results presented in Table 6. Overall, cognitive absorption construct appears to influence the training outcome (\( \beta = -0.13; \, p < 0.000 \)). The model explains 13% of the variance from the training outcome. Interestingly, while all the CA dimensions individually seem to predict the training outcome, the effect of perceived control seems to have the strongest effect (\( \beta = 0.16; \, p < 0.01 \)) with an explained variance of 19.0%. It must be noted that HRV has a significant negative effect on the training outcome (\( \beta = -0.06; \, p < 0.01 \)). In the model with the perceived control covariate, we noted that HR has a positive and significant impact on training outcome (HR \( \beta = 0.02; \, p < 0.05 \)); the other neurophysiological variables, as well as the skill and difficulty were tested and were not significant in this model. It is possible that the effect of cognitive absorption and training outcome is artificially suppressed if elements of the psychophysiology of the individual, such as HR and HRV, are not controlled for. In other words, HR and HRV might be suppressor variables that must be included in explaining training outcome in order to offset the suppression effect. The positive influence of HR and negative impact of HRV could suggest that some levels of arousal can also contribute to the training outcome, which is somewhat in line with the flow theory. These results are also in line with previous researches which suggest that the sensitivity of HRV could be tied to effective and efficient emotion regulation in contexts involving cognitive performance (Elliot et al., 2011) and self-regulatory strength (Segerstrom & Nes, 2007). Taken together, these results provide partial support for H2.

*** Insert Table 6 here ***
To summarize this section, Figure 2 illustrates the main relationship supported in this research.

*** Insert figure 2 here ***

6. Discussion and Concluding Comments

The objective of this research was to seek deeper insights into intrinsic motivating mechanisms, key determinants of learning achievement. By investigating neurophysiological correlates of CA in the context of enactive learning (specifically simulation-based training on the use of enterprise resource planning (ERP) software) our objective was to generate new insights into the psychological states that are conducive to experiencing this flow related state. In effect, our objective was to investigate the effects of neurophysiological correlates of cognitive absorption in an enactive learning context. Overall, the results suggest that cognitive absorption was positively related to a more relaxed, less vigilant state of the learner. Each of the five neurophysiological measures (EEG alpha, EEG beta, electrodermal activity, heart rate, and heart rate variability) explained significant and unique variance in cognitive absorption over and above the flow theory variances (skill, difficulty, and their interaction).

From a theoretical viewpoint, this study illustrates the opportunity to use the tools and theory from neuroscience to inform IS research. One opportunity of NeuroIS is to investigate unconscious and implicit antecedents to IS construct using neurophysiological measurements (Dimoka et al., 2011; Ortiz De Guinea et al., 2013). Based on the results of this study, adding the neurophysiological variables more than doubled the amount of explained variance in the predictive model of cognitive absorption. This result underscores the importance of considering neurophysiological variables within technology acceptance research.

Results suggest that perceived control appears to have the strongest effect on training outcome; moreover, it could be a mediator transmitting the indirect effects of these neurophysiological determinants on training outcome. In the educational literature, perceived control of the learning activities has been identified as predictor of student engagement (Deci et al., 1981; Grannis, 1978). Control perception has
already been reported in previous studies as an important determinant of various dependent variables in the ERP implementation studies (Schmidt, 2011). In the present study, perception of control is the strongest predictor of the training outcome in the simulation and appears to be a key dimension in a learner’s ability to demonstrate his competency at using IS. The model presented explains half of the variance of the control perception.

The direct effects of cardiovascular markers on training are interesting and necessitate further research, as this adds support to the value of using neurophysiological variables. These results suggest that, in addition to the perception of the learners, some levels of observable anxiety via cardiovascular results are required in order to achieve the training outcome. More research is needed to understand this effect.

As any research, this study has some limitations. Our sample is limited to university students, which may induce a general bias in the computer efficacy in our sample. While our sample size is consistent with previous research in NeuroIS (Riedl et al., forthcoming), future research should replicate this study with a more diverse group, such as employees using an ERP system in the workplace. Qualitative data analysis of user behavior using a video software analysis tool (such as Noldus Observer XT) could be used to help to better characterize the emotional valence of the subject (by coding their facial expression, for example). Moreover, for practical research purposes, only one EEG site was used for this study. Future research should also consider additional sites, such as frontal midline (Fz) which is related to short term memory load (Jensen & Tesche, 2002; Ortiz de Guinea et al., Forthcoming), a key differentiator between novices and experts (Hill & Schneider, 2006). Respiration could also be added in a future research to incorporate in the model Respiratory sinus arrhythmia, a marker related to mental workload (Cacioppo et al., 2007).

These findings not only contribute to the current call for research on end-user training, but also point to the importance of considering neurophysiological factors along with trainees’ experience and task
difficulty when developing effective IT curricula. Enactive training programs might be designed to induce neurophysiological states that will result in more efficient and better use of the technology. More broadly, establishing neurophysiological markers related to cognitive absorption and other cognitive and affective states linked to training effectiveness (such as perceived usefulness, perceived ease of use, computer anxiety, and frustration), promises to advance our understanding of the neural and developmental mechanisms underlying enactive learning. Such insights could open up new frontiers for advancing the development of more efficient, effective, and enjoyable. Given the continued high failure rate of new information systems implementations, much of which can be directly attributed to inadequate training practices, the quest for such insights warrants urgent attention.

7. References


StataCorp. (2007). *Stata Statistical Software: Stata 10 User’s guide* College Station, TX: StataCorp LP.


Figure 1: Research Model

- Difficulty
- Skill
- Difficulty x Skill
- EEG Alpha
- EEG Beta
- EDR
- HR
- HRV

Cognitive Absorption (CA)

H1A
H1B
H1C
H1D
H1E
H2
Training outcome
Figure 2: Summary of main results

- Difficulty: 0.72 (0.014)
- Skill: 5.23 (0.001)
- Difficulty x Skill: -1.97 (0.011)
- EEG Alpha: 2.73 (0.031)
- EEG Beta: -17.28 (0.024)
- EDR: -6.42 (0.045)
- HR: 0.05 (0.020)
- HRV: -0.06 (0.008)

Cognitive Absorption (CA)

R² = 34% (0.000)

Training outcome

R² = 13% (0.012)
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<th>Cognitive absorption (CA)</th>
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<th>Items</th>
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<td>3</td>
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<tr>
<td>CA_HE Heighted enjoyment</td>
<td>0.792</td>
<td>3</td>
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<tr>
<td>CA_CU Curiosity</td>
<td>0.914</td>
<td>3</td>
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<tr>
<td>CA_FI Focused immersion</td>
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<td>CA_CO Control</td>
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Table 2: Descriptive statistics and correlations

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<td>.47***</td>
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<td>-.20</td>
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<td>.14</td>
<td>.09</td>
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<td>-.03</td>
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<td>.04</td>
<td>.16</td>
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<td>Heighted enjoyment</td>
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<td>1.89</td>
<td>-.12</td>
<td>.27*</td>
<td>-.02</td>
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<td>.09</td>
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<td>-.15</td>
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<td>.16</td>
<td>.84***</td>
<td>.83***</td>
<td>.75***</td>
<td>.86***</td>
<td>.87***</td>
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</table>

Note: * p < 0.05; ** p < 0.01; *** p < 0.001.

EDR = Electrodermal response, Heart rate = HR, Heart rate variability=HRV, EEG = Electroencephalography
**Table 3: Comparative Effects of Difficulty, Skill and their Interaction Versus Psychophysiological Variables on Cognitive Absorption**

<table>
<thead>
<tr>
<th></th>
<th>Basic model</th>
<th>Model with Psychophysiological measures</th>
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<tr>
<td></td>
<td>Coef.   SE  P&gt;</td>
<td>Coef.   SE  P&gt;</td>
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<tr>
<td>Difficulty</td>
<td>0.94 0.365 0.007</td>
<td>0.72 0.313 0.014</td>
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<tr>
<td>Skill</td>
<td>6.78 1.708 0.000</td>
<td>5.23 1.472 0.001</td>
</tr>
<tr>
<td>Difficulty x Skill</td>
<td>-2.53 0.974 0.007</td>
<td>-1.97 0.820 0.011</td>
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<tr>
<td>EEG Alpha</td>
<td>2.73 1.411 0.031</td>
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<tr>
<td>EEG Beta</td>
<td>-17.28 8.378 0.024</td>
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</tr>
<tr>
<td>EDR</td>
<td>-6.42 3.683 0.045</td>
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</tr>
<tr>
<td>HR</td>
<td>-0.04 0.023 0.033</td>
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<tr>
<td>HRV</td>
<td>0.05 0.022 0.020</td>
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<tr>
<td>Constant</td>
<td>3.92 0.767 0.000</td>
<td>4.58 1.172 0.000</td>
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<tr>
<td>R²</td>
<td>0.16 0.002 0.002</td>
<td>0.34 0.002 0.000</td>
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*DV: Cognitive absorption. Repeated Measures (STATA CLUSTER ID). Directional hypothesis (One tail p values).*
Table 4: Comparative effects on Cognitive Absorption and Its Five Underlying Dimensions

<table>
<thead>
<tr>
<th></th>
<th>DV: Cognitive absorption (CA)</th>
<th>DV: Control (CA_CO)</th>
<th>DV: Curiosity (CA_CU)</th>
<th>DV: Temporal dissociation (CA_TD)</th>
<th>DV: Focus immersion (CA_FI)</th>
<th>DV: Heightened enjoyment (CA_HE)</th>
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<td>Coef.</td>
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<td>7.08</td>
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<td>0.011</td>
<td>-3.19</td>
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**DV**: dimensions of CA : CA_CO, CA_CU, CA_TD, CA_FI and CA_HE. Repeated Measures (STATA CLUSTER ID). Directional hypothesis (One tail p values).
## Table 5: Summary of results

<table>
<thead>
<tr>
<th></th>
<th>Cognitive Absorption (CA)</th>
<th>Control (CA_CO)</th>
<th>Curiosity (CA_CU)</th>
<th>Temporal dissociation (CA_TD)</th>
<th>Focus immersion (CA_FI)</th>
<th>Heightened enjoyment (CA_HE)</th>
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<tr>
<td>EEG Alpha</td>
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<td>+</td>
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<td>NS</td>
<td>NS</td>
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<td>EEG Beta</td>
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<td>-</td>
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<td>HR</td>
<td>-</td>
<td>NS</td>
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<td>NS</td>
</tr>
<tr>
<td>HRV</td>
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<td>NS</td>
<td>+</td>
<td>NS</td>
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<td>48,9 %</td>
<td>18,3 %</td>
<td>21,2%</td>
<td>31,0 %</td>
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<tr>
<td>Variance explained by neurophysiological variables</td>
<td>27,7 %</td>
<td>14,2 %</td>
<td>6,8 %</td>
<td>17,0 %</td>
<td>4,0 %</td>
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Table 6: Comparative Effects of Cognitive Absorption and Its Dimension on Training outcomes

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<th></th>
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<th>With curiosity (CA_CU)</th>
<th>With temporal dissociation (CA_TD)</th>
<th>With focus immersion (CA_FI)</th>
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$DV =$ Training outcomes. Repeated Measures (STATA CLUSTER ID). Directional hypothesis (One tail p values).