

**THE EFFECTS OF CONTINUOUS ADAPTATION  
OF ONLINE CONTENTS BASED ON THE  
APTITUDE PROFILE ON LEARNERS'  
ENGAGEMENT**

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by

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**KESAN ADAPTASI BERTERUSAN DALAM KANDUNGAN ATAS TALIAN  
BERDASARKAN PROFIL KEBOLEHAN TERHADAP PENGLIBATAN  
PELAJAR**

**ABSTRAK**

Perbezaan dalam ciri pembelajaran dan keutamaan di kalangan individu boleh dikaitkan dengan perbezaan dalam pembentukan kapasiti model mental yang membolehkan individu melaksanakan tingkah laku tertentu. Model mental ini dipercayai menyediakan logik asas untuk pemprosesan maklumat individu. Kecenderungan tingkah laku ini secara tidak langsung dikaitkan dengan keupayaan seseorang untuk terlibat secara kognitif dalam proses pembelajaran tanpa gangguan oleh rangsangan lain. Kajian literatur menunjukkan bahawa mekanisme terkini dalam sistem penyesuaian tidak berterusan menyokong peraturan tugas rumit dalam sesi pembelajaran yang berturutan. Oleh itu, pelajar mungkin mendapati diri mereka tidak dapat terus maju dalam sesi pembelajaran kerana ketidaksesuaian antara kebolehan kognitif mereka dan kerumitan tugas. Ini mendorong penyelidik untuk mengkaji bagaimana peningkatan tumpuan pelajar, emosi, dan beban kognitif, menggunakan mekanisme adaptasi berterusan dalam kandungan pembelajaran atas talian, boleh menyumbang kepada penglibatan mereka. Sistem penyesuaian berterusan atas talian untuk menggalakkan penglibatan dibangunkan berdasarkan premis perubahan tahap kebolehan pelajar. Peraturan kerumitan perwakilan disesuaikan untuk menilai pelajar dengan tingkat kebolehan rendah, sederhana, dan tinggi. Seramai 41 orang pelajar (87.80% lelaki dan 12.20% perempuan; berumur 20-25 tahun) mengambil bahagian dalam sesi pembelajaran atas talian yang berkaitan dengan tiga konsep pengaturcaraan.

Elektroencephalogram kuantitatif (qEEG) digunakan untuk menganalisis aktiviti elektrik dalam minda pelajar semasa belajar menggunakan sistem yang dicadangkan. Keputusan menunjukkan bahawa sistem yang dicadangkan berjaya meningkatkan beban dan tumpuan kognitif pelajar, yang seterusnya meningkatkan penglibatan mereka. Di samping itu, emosi didapati tidak mempunyai kesan yang signifikan terhadap beban kognitif pelajar. Keputusan analisis varians berulang menunjukkan bahawa tahap kebolehan mempunyai pengaruh yang lebih kuat terhadap pengaktifan otak pelajar dari segi tumpuan, beban kognitif, dan penglibatan. Adalah diandaikan bahawa sistem yang dicadangkan dapat membantu pelajar untuk memproses bahan pembelajaran yang diberikan dengan berkesan berdasarkan tahap kebolehan mereka. Penemuan terkini boleh digunakan sebagai asas untuk menggalakkan pembelajaran atas talian berkaitan tugas rumit. Ia juga boleh digunakan untuk memaklumkan pereka dan pemaju sistem pembelajaran tentang kepentingan mengawal selia kerumitan tugas mengikut profil kebolehan pelajar. Ini akan membantu pelajar memproses maklumat yang dipersembahkan secara bermakna dan membuat kesimpulan yang diperlukan untuk memahami kandungan pembelajaran.

# **THE EFFECTS OF CONTINUOUS ADAPTATION OF ONLINE CONTENTS BASED ON THE APTITUDE PROFILE ON LEARNERS' ENGAGEMENT**

## **ABSTRACT**

The differences in learning characteristics and preferences among individuals can be attributed to the differences in the formation of the capacity of the mental model that enables the individual to undertake a certain behavior. This mental model is believed to provide the basic logic for individual processing of information. The tendency of this behavior is somehow associated with one's ability to cognitively engage in the learning process without being distracted by other stimuli. Literature shows that the current mechanisms in adaptive systems do not continuously support the regulation of the complexity of the task in a sequential learning session. Thus, learners may find themselves unable to continuously progress in a learning session due to the misfit between their cognitive abilities and the complexity of the task. This led the researcher to examine how the promotion of learners' concentration, emotion, and cognitive load, using a continuous adaptation mechanism of online learning contents, can contribute to their engagement. An online continuous adaptive system for promoting engagement was developed based on the premises of changes in learners' aptitude level. The regulation of the representation's complexity was customized to suite the learners with a low, medium, and high aptitude level. A total of 41 students (87.80% male and 12.20% female; aged 20–25 years) participated in online learning sessions related to three programming concepts. The quantitative electroencephalogram (qEEG) was used for analyzing the electrical activity in the students' brain while learning in the proposed system. The results showed that the

proposed system successfully promoted students' cognitive load and concentration, which in turn improved their engagement. Additionally, emotion was not found to have a significant effect on students' cognitive load. Results of the repeated measures analysis of variance revealed that the aptitude level had a significantly stronger influence on students' brain activation in terms of concentration, cognitive load, and engagement. It is assumed that the proposed system helped learners to effectively process the given learning materials according to their aptitude level. The present findings can be used as the basis for promoting students' online learning of complex tasks. It can be also used to inform designers and developers of learning systems about the importance of regulating task complexity according to the learners' aptitude profile. This would help learners to process the presented information meaningfully and to make the inferences necessary for understanding the learning content.

# **CHAPTER ONE**

## **INTRODUCTION**

This chapter introduces the main elements of this study, including the research background, problem statement, and research aims. It also characterizes the formation of the conceptual framework of the study and its significance in the field of science learning.

### **1.1 Overview**

The demand for providing effective mechanisms to aid learning in online adaptive systems has increased lately. Current research on adaptive systems has long been driven by pre-defined characteristics that represent individuals' mental model for undertaking certain learning activities (Stern & Woolf, 2000). For instance, learners' state of emotion and cognition has been extensively utilized as the criterion in the design of current adaptive systems. It involves extracting alternative inputs (personality, performance test, cognitive style, etc.) from learners to suggest a learning session that characterizes the individual's preferences based on these inputs.

The differences in the learning characteristics and preferences of individuals can be attributed to the differences in the formation of their mental model capacity to undertake a certain behavior, which is believed to provide the basic logic for information processing (Becker, 2005) and decision making (Barrales-Molina, Benitez-Amado, & Perez-Arostegui, 2010). The tendency is somehow associated with one's ability to cognitively engage in the learning process without being distracted by

other stimuli. This notion helped the researcher to develop an argument for how the promotion of learners' concentration on a task can contribute to the cognitive process by helping learners to actively engage throughout the phases of that task. The same is true for emotion. Isaacowitz, Charles, and Carstensen (2000) have provided evidence on the role of emotional changes in influencing one's performance on traditional cognitive tasks. Therefore, the present researcher was motivated to investigate the potential of regulating the complexity of a learning task to stimulate learners' concentration, cognitive load, and emotion. It is also argued here that such regulation of the task complexity can substantially drive their cognitive ability to process information, and as a result, maintain learners' engagement throughout the task. From the literature, it was found that learning programming is one of the ongoing obstacles in which learners cannot easily respond to the cognitive demands required to engage in a learning task. For instance, some researchers like Hsieh, Lee, and Su (2013) stated that computer programmers not only serve as core players in the development of the software industry, but they also exert a significant impact on extending the knowledge regarding computer software. The core component of computer courses is associated with teaching and learning programming skills. Meanwhile, programming skills are also required for students of natural sciences, mathematics, and engineering programs. A long time ago, Foreman (1988) stated that learners should consider acquiring the knowledge and skills necessary for the development of computer expertise, which serves as a key prerequisite for a comprehensive understanding of computer science. The current efforts for providing a flexible learning environment for students have opened the doors for developing various learning techniques. Despite the fact that computer programming is considered as a core subject for students in computer science, learning it is far from easy (Tennyson, 2013).

In recent years, the focus of the development of adaptive learning environments has shifted from basing them on users' progress to focusing more on behavioral contexts. Such learning contexts were designed with the aid of Internet and multimedia technologies, which extensively helped map the methods of acquiring knowledge through different means such as e-learning, e-courseware, and m-learning. These methods are currently used as alternative tools for traditional classroom (Dragon et al., 2013).

With current demands for considering cognitive aspects in computer science students' learning, the current focus has moved toward using intelligent and awareness based learning environments (Aleven & Koedinger, 2002; Mavrikis, Gutierrez-Santos, Geraniou, & Noss, 2013). Hence, studying the role of cognitive load in these environments can help form a better understanding how one can learn effectively. Although several studies have suggested the benefits of developing an e-learning system for instruction, these systems are still posing some problems for learners, including those related to learner control, disorientation, and cognitive overload (Holley, 2002; Hemsley, 2002; Standen, Brown, & Cromby, 2001). The review of the literature showed that emotion, concentration, and cognitive load have a strong link when it comes to explain the aptitude of a person in a learning situation. And these variables were also hypothesized in the current study model to explain their influence on students' engagement. Therefore, the main issue associated with promoting one's cognitive states and its impact on students' engagement have been covered in the next section.

## **1.2 Research background**

Many scholars have claimed that students who learn from receiving information passively can still improve their learning capacity by learning actively (Chi & Wylie, 2014). “Active learning” is defined as learning that requires students to cognitively engage with the learning material (Bonwell & Eison, 1991). This includes getting students involved with the information presented by allowing them to truly analyze, synthesize, and evaluate the material rather than just passively receiving it (Faust & Paulson, 1998). Hence, students who cognitively engage with the task are considered to be actively involved in it. Based on this definition, teachers attempt to create excitement in the classroom. However, its role in the online learning environment is rarely discussed. Previous studies have examined individuals’ engagement using different motivational perspectives (Blumenfeld, Kempler, & Krajcik, 2006; Raes & Schellens, 2012), the behavioral perspective, or the emotional perspective (Dolan, 2002; Wang & Eccles, 2012).

On the other hand, improving students’ learning performance on a complex learning task has always been associated with the level of engagement one attains when learning. This is the core focus of science domains as the emphasis has moved from teaching complex learning strategies to teaching via complex learning (Dietterich & Bakiri, 1995). Many scholars have proposed learning techniques to support the current teaching scenario in science related subjects, particularly in mathematics and computer programming (D’Mello & Graesser, 2012; Schoenfeld, 1992; Silver, 2013). The focus on teaching computer programming through problem-solving contexts and enquiry-oriented environments has proven its efficiency a long time ago, and this method is assumed to enable students gain a deeper understanding of programming logic and

processes in a fixed environmental setting (Dale & Weems, 2005; Webb, Ender, & Lewis, 1986). However, owing to the shift toward the utilization of technology in systems based on the awareness of the context, introductory programming courses have become considerably difficult for many students, often resulting in low retention rates (McDowell, Werner, Bullock, & Fernald, 2006). This impact of the level of difficulty of courses, which emphasizes on the role of cognition in how students learn computer programming, has been acknowledged in the literature since 1981 (Pea & Kurland, 1984).

However, some previous efforts have accurately addressed these difficulties. For instance, McCracken et al., (2001) conducted a multi-nation, multi-institution study on the assessment of programming skills of first-year Computer Science (CS) students. They highlighted the problems faced by students in the early stages of learning programming, particularly those related to tracing (or “desk checking”) through codes and understanding their logical construction. This problem is caused, in part, by the inherent difficulty of the programming task through which the students are required to learn how to interpret and work with many new, abstract, and interdependent concepts that have a static as well as a dynamic component. Petre and de Quincey (2006) attributed such problems to the ill-defined and complex visualization of code sequences. This level of inherent complexity is widely recognized in the literature (Kim & Lerch, 1997). Furthermore, the literature suggests that a programming task typically demands complex cognitive skills such as procedural and conditional reasoning, planning, and analogical reasoning (RMayer, 2013; Moons & De Backer, 2013). Of course, besides the inherent difficulty of the subject, the problem could also be caused, in part, by an incorrect way of teaching this subject. In the past decades,

many researchers have suggested different ways to improve the performance of students by making changes to the way the programming subject is taught. For example, some studies have suggested improving the visualization of programming codes by using different design principles (Blackwell, McLean, Noble, & Rohrhuber, 2014; Ferreira et al., 2012; Lau & Yuen, 2011; Li & Watson, 2011; Martin, Berland, Benton, & Smith, 2013; Moreno, 2012; Siegmund et al., 2014; Yousoof & Sapiyan, 2015). This led the present researcher to argue that such interventions can be achieved through promoting one's emotional state and concentration to actively process the cognitive load that is required for sustaining an adequate level of engagement when learning programming.

However, few studies have looked at the role of emotion, cognition, and behavior in driving engagement when learning with hypermedia education systems, which relies on learning approaches that are usually confusing for learners (Hsieh et al., 2013). For example, most traditional education systems provide the same content and the same set of links to all learners. Consequently, the materials may not necessary fit the learners' needs within a particular learning session (Qu, Wang, & Zhong, 2009). Since the present study aimed to utilize the current state of online learning adaptive systems for assessing learners in a variety of areas (Beldagli & Adiguzel, 2010), it become viable to study the potential of continuously regulating learning materials to fit students' cognitive ability when learning programming.

### **1.3 Problem statement**

The present study attempted to solve the current unresolved problems related to sustaining learners' engagement in an online environment (Moons & De Backer,

2013). When students engage in online learning sessions, their cognitive load is expected to influence their level of engagement (Berka et al., 2007; Kirschner, Kester, & Corbalan, 2010; Leppä, Kettunen, & Sihvola, 2011) because the current mechanisms in adaptive systems do not support effective procedural learning by regulating the complexity of the learning task continuously, especially at the early stages of learning. As such, learners may find themselves unable to continuously progress in a complex learning session due to the misfit between their skills and the given task.

This belief can be applied to CS courses, which have always been perceived to involve tasks with high cognitive load that require students to perform a sequence of operations. Recently, many studies have attempted to examine several techniques for activating one's cognition within the task in an online learning environment. For instance, Guzdial (2015) revealed the difficulties in learning CS subjects due to the complexity of the learning sequence, including the amount of information presented to a user. Moons and De Backer (2013) attributed some of these difficulties to the lack of effective tools for maintaining students' cognitive load. Procedural learning usually requires repetition of an activity, and the associated learning is demonstrated through improved task performance (Koziol & Budding, 2012). In this regard, Taraban et al., (2007) emphasized on the current lack of research to enrich procedural learning scenarios offered to students in their early learning stages.

Based on these observations, the present researcher realized that most of the difficulties experienced by university students when learning programming concepts may be attributed to the complexity of these concepts and method of delivery. The researcher's review of the extant literature linked such difficulties to the lack of

considering the relationship between students' behavior and cognition, including attention, working memory, and cognitive load, when interacting with the system. As such, learners may find themselves unable to undertake a certain learning session due to the misfit between their cognitive abilities and task complexity. Therefore, the present study aimed to examine the impact of customizing learning resources related to a programming task continuously through the learning sessions, based on the changes in learners' cognitive aptitude. This mechanism was named as the continuous adaptive system (CAS) (see operational definition).

#### **1.4 Research objectives**

The goal of this study was to develop a new way for customizing the complexity of online learning systems according to the learners' aptitude level. In addition, this study aimed to achieve the following objectives:

- 1- To develop an online continuous adaptive system for promoting students' engagement.
- 2- To investigate the effects of changes in students' concentration from using the online continuous adaptive system on their cognitive load and engagement when using the CAS.
- 3- To investigate the effects of changes in students' emotion from using the online continuous adaptive system on their cognitive load and engagement when using the CAS.
- 4- To investigate the effects of changes in students' cognitive load from using the online continuous adaptive system on their engagement when using the CAS.

## **1.5 Research questions**

Based on the above-mentioned objectives, the researcher attempted to answer the following research questions:

- 1- How can students' engagement be improved by using the CAS?
- 2- What are the effects of changes in students' concentration from using the online continuous adaptive system on their cognitive load and engagement when using the CAS?
- 3- What are the effects of changes in students' emotion from using the online continuous adaptive system on their cognitive load and engagement when using the CAS?
- 4- What are the effects of students' cognitive load on their engagement when using the CAS?

## **1.6 Conceptual framework**

This study was based on the Cognitive Load Theory by Sweller (1988), Relational complexity Theory by Halford, Wilson, and Phillips (1998), and Cognitive Aptitude Theory by Snow (1992).

Chandler and Sweller (1991) described how the cognitive load theory can be used to formulate the way in which cognitive resources are absorbed when learning about a topic. Based on this, it was proposed to embed several learning and problem-solving procedures in instructional formats to help sustain the student's focus and engagement with the cognitive activity pertaining to the goals of the task. The researcher's review of the literature revealed an apparent lack of clarity about the relationship between cognitive demands of certain tasks and one's learning of these tasks. For example, one

can find many experiments that demonstrate that conventional problem solving can have negative learning consequences. This body of evidence questions the usefulness of solving large numbers of conventional problems (in the areas of mathematics and science) (Ward & Sweller, 1990).

From the literature, it is evident that the use of detailed explanation supported with examples may significantly facilitate learning than the conventional emphasis on solving a large number of problems does (Atkinson, Derry, Renkl, & Wortham, 2000). Researchers like Chi, Bassok, Lewis, Reimann, and Glaser (1989) acknowledged the effect of cognitive differences in learning based on their finding that students with high cognitive ability performed better than did those with poorer cognitive abilities in terms of obtaining a detailed explanations of worked examples. This underscores the need for a researcher to consider regulating the complexity of the learning task to evoke a certain ability needed to properly process the learning materials. Thus, the present researcher used the cognitive load theory to clarify why worked examples can facilitate learning as compared to problem solving (e.g., Paas, Renkl, & Sweller; 2003). This includes strengthening learners' concentration to enable them to mentally integrate the various sources of information. Such processes impose certain searching demands that help the learners to comply with the goals of the learning task (Van Merriënboer & Sweller, 2005).

In addition, Fraser et al., (2012) revealed that the relationship between emotions and learning is more complex, especially when students encounter different cognitive demands. Although there are relatively consistent data indicating that heightened negative emotions, such as anxiety, typically hinder learning by generating an extraneous cognitive load, the effect of such consequences on sustaining students'

engagement in the online context is less studied. Meanwhile, studies on emotion and cognitive load have shown that, when a person processes positive emotions, the learning tends to improve (Fraser et al., 2012). This effect can be attributed to the substantial increase in motivation and enhancement of problem solving. However, the environmental conditions required for promoting positive emotions in an online mediated environment are unclear. Nevertheless, it has been suggested that all emotions generate an extraneous cognitive load, and thus, the net effect of positive emotions may depend upon their interactions with other sources of cognitive load (Fraser et al., 2012). There is little evidence to explain how positive emotions can be facilitated, and what impact it has on one's cognitive load. Therefore, in the present study, the researcher assumed that regulating the complexity of online content can help foster learners' positive emotion toward learning. This can be established when learners with different cognitive abilities experience different cognitive behaviors that may or may not drive their concentration and emotion within the task.

On the other hand, Moons and De Backer (2013) stated that working memory load can be reduced significantly by integrating visual guides such as diagrams and textual statements, or, as Sweller (2004) suggested, when learners are not required to split their attention between two physically separated representations of information. For novice programmers, cognitive load surely is high. Bailie, Courtney, Murray, Schiaffino, and Tuohy (2003) illustrated this problem as follows: "from the first line of a Java program, you know we are in serious trouble [public static void main (java code)]."

Magner, Schwonke, Alevén, Popescu, and Renkl (2014) investigated the effect of interesting decorative illustrations on immediate and delayed learning performance. The researchers found that decorative illustrations resulted in lower transfer for the students who had low levels of prior knowledge, but it supported students who had very high levels of prior knowledge. Park, Moreno, Seufert, and Brünken (2011) found that seductive details either hindered or fostered learning, depending on the level of cognitive load they induced. Taken together, these findings suggest that the cognitive processes of selecting and aggregating relevant information into a coherent mental model can not only be affected negatively by seductive details or decorative illustrations, but that it can also influence learners positively if they have sufficient available resources to process non-redundant and interesting, but irrelevant, learning material. Thus, according to multimedia learning principles, cognitive resources may be available as a result of optimized design of the learning environment (Mayer, 2005).

In computer-based learning environments, Reed, Burton, and Kelly (1985) highlighted the possible relationship between the use of dual-task design on cognitive engagement for different computer-based writing tasks with different levels of difficulty. The literature also showed that online engagement of learners can be increased from the easiest task that induced a low level of cognitive load to the moderately difficult task with a medium level of load (Brunken, Plass, & Leutner, 2003). Siegle, Ichikawa, and Steinhauer (2008) asserted that a person can experience low cognitive capacity when engaging in an active learning task that provokes relatively low levels of cognitive load. Such behavior can be explained by the relational complexity theory, which attributes the impact of task complexity to the developmental changes in the

theory of mind. It is evident that, when a person engages in less complex tasks or transformation tasks, he/she will be able to gradually understand the taught concept.

This led the present researcher to conclude that inferring the cognitive state of students in procedural learning of programming tasks could provide affective mediation for enhanced performance, through which cognitive aptitude can be used to regulate the learning resources needed to understand the programming concepts. Such a state can be predicted based on the aptitude level of a person when learning the task, as explained by the Cognitive Aptitude Theory proposed by Snow (1992). Therefore, the present researcher assumed that providing users with different levels of task complexities can help them to learn and accommodate descriptive and prescriptive goals pertaining to their aptitude.

Based on these observations, the conceptual framework was constructed to reflect the potential of adjusting the task complexity according to the learners' aptitude level. Aspects related to students' emotion, concentration, and cognitive load were proposed to be the main drivers of learners' online engagement with adaptive systems. Additionally, an electroencephalogram (EEG) was used to capture these aspects using an emotiv device, as shown in Figure 1.1.

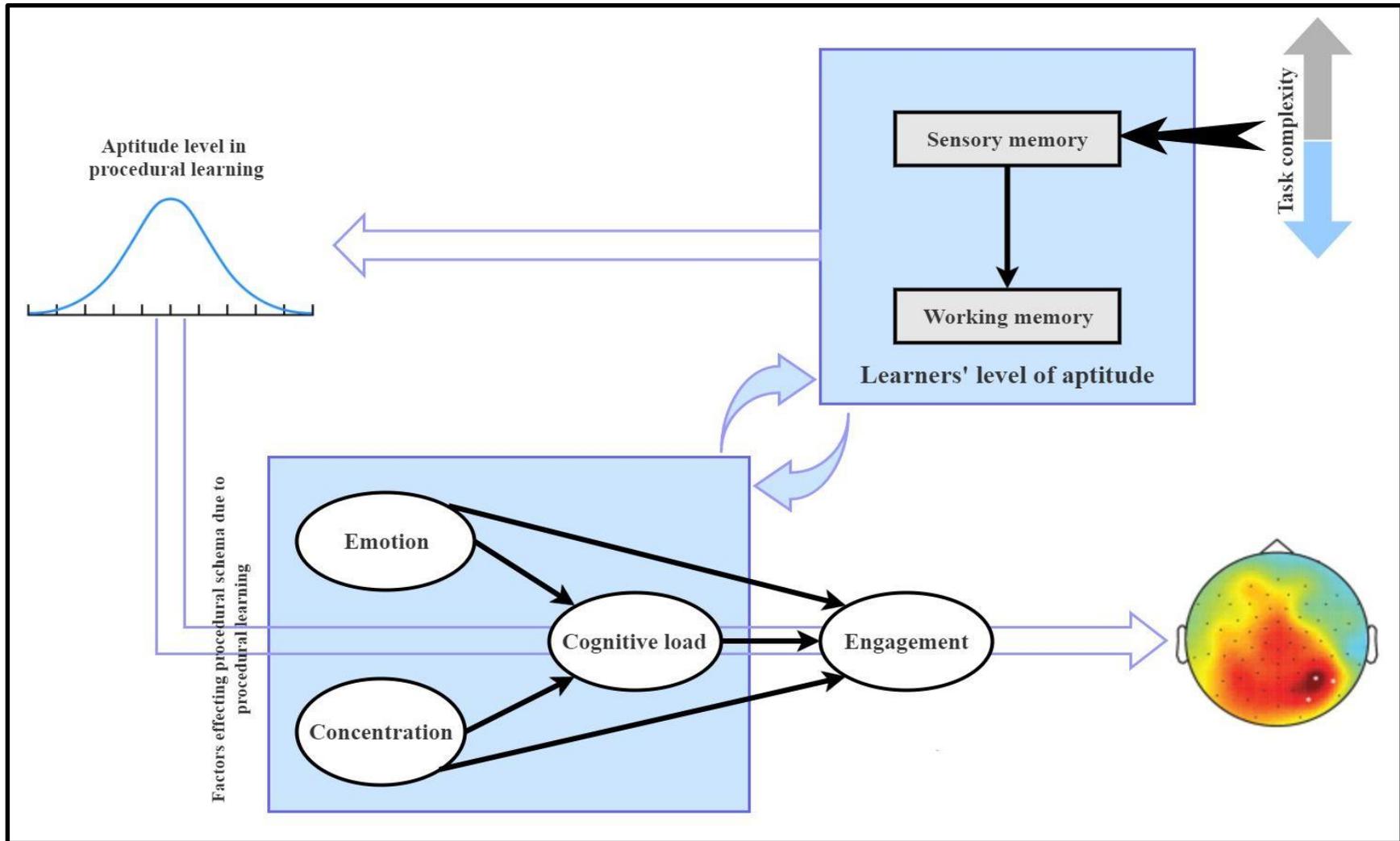


Figure 1.1: Conceptual framework

## **1.7 Significance of the present study**

It is argued that continuously regulating the complexity of the learning content based on the learners' aptitude level can increase their concentration and can elicit emotions in ways that will facilitate learning. This learning experience is believed to stimulate a steady cognitive load throughout the learning sessions, and hence, sustain/increase students' online engagement. The present study aimed to extend the current understanding on how learners with definite cognitive abilities can be supported in particular learning tasks. This involved examining the interaction between the cognitive process demands when learners engage in a programming task. This is believed to offer an insightful way for reengineering the current representation of online adaptive systems. The current study adds to both learning and instructional theories by considering new mechanism that influence the learners' engagement in online environment though assessing the task complexity continuously based on their level of aptitude. Considering that, in current systems, cognitive abilities are assessed only partially, this study further explored the potential of continuously adjusting content complexity to sustain/increase engagement.

## **1.8 Operational definitions**

**Adaptive system:** It is a system that changes its behavior in response to its environment. The adaptive change that occurs is often relevant to achieving a goal or objective (De Lemos et al., 2013).

**Continuous adaptive system:** In this study, this term is used to refer to the system that changes the complexity of the learning task in response to the level of one's aptitude in multiple learning sessions. Specifically, in the present study, the researcher

attempted to regulate the complexity of a programming task continuously, to promote learners' behavior, emotion, and cognition.

**Emotion:** It is an acute and intense psycho-physiological reaction to significant objects or events and it consists of multi-dimensional constructs (Artino & Jones, 2012). It is a temporal experience and a reaction to certain events (Scherer, 2005). In this study, the power spectrum of the EEG was used to quantify the effect of the CAS on learners' emotion when learning about programming. The measurement of the learners' emotion was based on the arousal equation suggested by Ramirez and Vamvakousis (2012).

**Concentration:** It is the ability of an individual to focus and be clearly aware of a stimulus. It is a significant psychological task in learning. In this study, EEG was used to quantify the effect of the CAS on the learners' level of concentration when learning about programming. The concentration index for each learner was obtained based on the equation developed by Sung, Cho, and Um (2012), which contains the main brain bands to be used for estimating the level of concentration.

**Cognitive load:** It is the amount of mental effort required to locate specific information and to understand how this information is oriented within a larger information source (Eveland & Dunwoody, 2001). In this study, EEG was used to quantify the effect of the CAS on the learners' cognitive load based on the formula proposed by Antonenko, Paas, Grabner, and van Gog (2010).

**Engagement:** It is the extent to which students are willing and able to take on the learning task at hand (Rotgans & Schmidt, 2011a). In this study, EEG was used to quantify the effect of the CAS on the learners' engagement based on the formula proposed by Pope, Bogart, and Bartolome (1995).

**Cognitive aptitude:** It is the process related to the estimation of one's brain's capacity for enhancing functional connectivity or communication between the cortical regions that are relevant to the cognitive demands, while attenuating irrelevant communication (Silberstein, 2006). In the present study, cognitive aptitude was used to identify the level of complexity of the content of a learning task by allowing learners to undertake a series of tests that are used to evoke their ability to perform the upcoming task. Additionally, cognitive aptitude was categorized into the three levels of high, medium, and low in this study.

## **1.9 Summary**

This chapter illustrated the motivation for conducting this study, along with the potential key challenges that online learners may face when learning programming concepts using the current learning methods. The researcher noted that ways to improve the learning process associated with programming has been researched widely lately, due to its significant implication for students' learning. Despite these efforts, current tools are still unable to maintain a steady cognitive state in students, to effectively improve their learning performance. Various researchers addressed this lack as the failure of current applications to consider the cognitive and behavioral aspects of learners while learning. Therefore, the present study proposed an alternative mechanism for regulating the complexity of a learning task based on the continuous

examination of learners' cognitive aptitude. The next chapter describes the theoretical understanding behind this study, along with the formation of the research hypotheses.

# **CHAPTER TWO**

## **LITERATURE REVIEW**

This chapter provides an in-depth insight on the current research gaps in providing an alternate solution for university students' learning of programming. It also examines the potential of the complexity theory and cognitive load theory to provide a clear view about the relationships between the variables examined in the present study.

### **2.1 Introduction**

In this chapter, the researcher aims to address the literature related to this area of research, in chronological order. The researcher focuses on two aspects in this chapter. First, he aims to determine the suitable cognitive trait that can be used to explain or differentiate one's cognitive ability in a learning context. Second, he aims to identify the suitable variables for interpreting learners' learning engagement in a particular system by considering the cognitive trait necessary for forming learning pedagogy, in order to regulate the complexity of learning content. The researcher started by categorizing the idea behind the structure and capacity of working memory based on the findings of previous scholars like Miller (1956). An exploration of up-to-date research related to the human information processing is introduced, with focus on the workings of the memory capacity and storage limitations. On the other hand, the applicability of the cognitive load theory, relational complexity theory, and cognitive aptitude theory has been explored in this chapter.

## 2.2 Cognitive traits

The association between cognitive traits and educational philosophy has been extensively addressed by previous studies. For example, Miller (1956) explained that the process of acquiring information is affected by the quantity of information that is necessary to choose one from a pair of equally different options pertaining to the nature of the task. He then extended this view by presenting a more precise understanding of working memory based on the results of several experiments that assessed the absolute judgment associated with unidimensional stimuli, which appeared to be irrelevant to the judgments used to decide among multidimensional stimuli. He stated that the process of scanning the presented information basically deals with the person's ability to judge the complexity of a situation. Miller (1956) further added that this scanning is commonly associated with immediate memory that imposes serious limitations on the quantity of information that humans can perceive, process, and remember. Based on this, it can be concluded that organizing a particular stimuli in several pieces or chunks can help stimulate and improve personal judgment about the learning materials, whereas the period of self-judgment and the short-term memory span are increased significantly.

Baddeley (1992) later purported the multicomponent model, which emphasizes on memory workflow while processing a bit of information. His model, shown in Figure 2.1, consists of episodic buffer and two systems that are commonly labeled as "*slave systems*" and another central system, labeled as the "*executive system*," which is responsible for controlling the communication flow between the slave systems. This includes managing the cognitive processes when more than one task is engaged in simultaneously. These systems involve a phonological loop that aims at storing the

phonological information and averts the decay of such information by refreshing it regularly. It also consists of a visuospatial sketch pad which aims at storing visual and spatial information that is used to form visual images based on the association between shape, color, and texture. The episodic buffer acts as a temporary memory which communicates with both long term memory and the components of working memory. It has the ability to merge information from the subsidiary systems, and from long-term memory, into a unitary episodic representation.

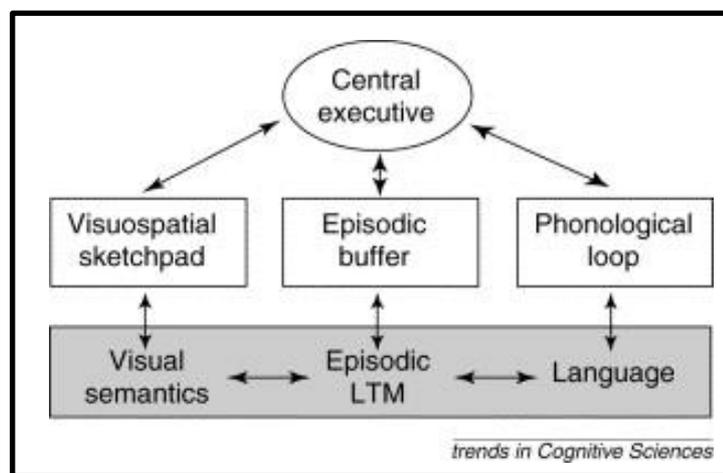


Figure 2. 1: The working memory model as proposed by Baddeley (1992)

Recently, McVay and Kane (2012) explained how some individuals are better than others when it comes to processing a piece of information. Based on this, a possible variation in one's comprehension can be predicted by measuring working memory capacity.

Based on these views, the present researcher was interested in exploring the potential of regulating the representation of information based on the association between memory capacity-based complexity and individual differences in cognitive aptitude, as introduced by the executive attention theory of Kane et al., (2004).

According to this perspective, the working memory performance in complex learning task requires metacognitive/executive processes in order to foster learners' ability for maintaining engagement with the learning tasks. With this in mind, maintaining engagement is necessary in order to promote learning. Most interface and system designers are concerned about doing the same within and between sessions (Bickmore, Schulman, & Yin, 2010). Such understanding was always found to be associated with emotional regulation (Fernandez-Duque, Baird, & Posner, 2000). Additionally, neuroimaging studies of the *Stroop effect* have confirmed the activation of the attentional system in understanding the word and color conflict (Hope, 2013; Ihnen, Petersen, & Schlaggar, 2015; Liu, Banich, Jacobson, & Tanabe, 2004; West & Alain, 2000), as shown in Figure 2.2a and Figure 2.2b. Thus, the activation of midfrontal areas in the human brain usually requires the individual to strike a balance between cognitive and emotional regulation, which, as a result, influences his/her commitment to the task. Hence, the role of regulating cognitive aptitude to improve concentration and emotion pertaining to a task is still unknown. However, previous experiments (e.g., Canli et al., 2005; Lavie, 2005; Schmeichel, 2007) have demonstrated a certain amount of structural differentiation, given the evidence that activation of attention and emotional areas can influence the capacity of the executive system to some extent.

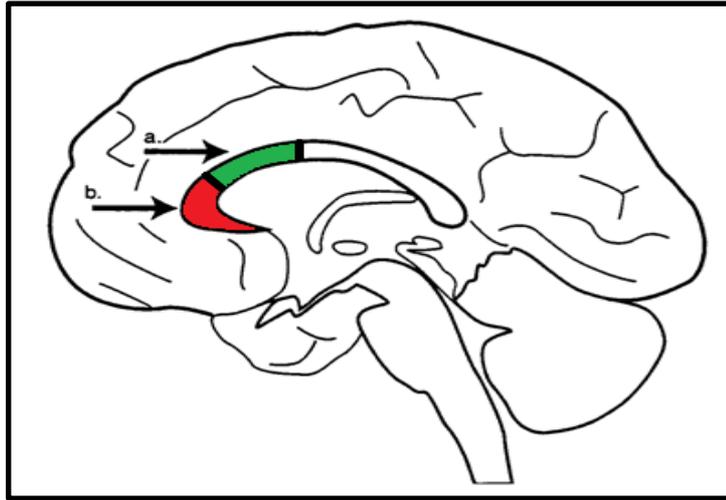


Figure 2. 2: Areas of the anterior cingulate activated by a cognitive task (a) and by an emotional task (b) (adapted from Bush et al., 1998)

Van Dijk, Kintsch, and Van Dijk (1983) were the first to identify the association between different cognitive processes that typically occur during basic processing. They identified several tasks related to perceptual features, linguistic features, propositional structure, macrostructure, situation model, control structure, goals, lexical knowledge, frames, general knowledge, and episodic memory of prior text. Consequently, each of these tasks would impede the limited capacity of the working memory. This led researchers like Cowan (1988) to investigate the concept of memory storage, selective attention, and their constraints within human information processing. Cowan (1988) stated that, when a person processes a certain volume of information within his/her cognitive capacity, it would stimulate the level of attention on that information.

Other previous scholars like Baddeley (2000) expanded the current views on the limited capacity of the working memory, which offers temporary storage of a multimodal code that is necessary for binding information from the initial subsystems, and long-term memory. In addition, the primary characteristics of Baddeley's model

pertain to an individual's attention on the process of information integration rather than on viewing the sub-systems in isolation. This perspective reveals the importance of identifying the link between long-term memory and the sub-systems.

From the learning perspective, Laurillard (1999) examined the common pedagogic strategy that is usually utilized in higher education, and she argued that the strategies embedded in a learning system must allow the learners to interpret a complex situation effectively, for them to comprehend the correct meaning of the educational content.

Laurillard's (1999) work was based on La Pointe and Engle (1990) viewpoint that pertained to the variation in cognitive capacity while processing information in simple and complex scenario. Later, Cowan et al., (2005) discussed the capacity of attention from the perspective of working memory and cognitive aptitudes, whereas Kintsch (1994) extended it to the promotion of learning in complex tasks by allowing learners to construct an episodic structure while learning. This includes presenting learning content that accommodates learners' needs to form an episodic structure that enables them to use long-term working memory on a daily basis. On the other hand, Seufert, Schütze, and Brünken (2009) discussed the importance of aptitude for facilitating learning based on the association between learners' cognitive state and the learning task. These observations were consolidated by Sharek and Wiebe (2014), who found a link between aptitude and engagement.

Based on these observations, the current study mainly aimed to improve learners' engagement in an online learning environment by considering the role of regulating learning content based on the learners' cognitive aptitude. This was assumed to