Education and Information Technologies (2019) 24:2763–2777
https://doi.org/10.1007/s10639-019-09895-2

The effectiveness of an online learning system based on aptitude scores: An effort to improve students' brain activation

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Received: 5 October 2018 / Accepted: 27 February 2019 / Published online: 6 March 2019

Abstract

The differences in learning preferences can be attributed to the differences in individuals' cognitive capacities which may lead them to undertake a certain behavior. It is argued that characterizing the learning complexity based on the volume of information presented to learners can eliminate any avoidable load on working memory. This study examined the effectiveness of an online continuous adaptive mechanism (OCAM) based on changes in learner aptitude scores across learning sessions. The representation of the learning content in these sessions was designed for a low-, medium-, and high-aptitude individual. The brain activation of 12 students (6 male and 4 female; aged 20–25 years), obtained from using the proposed system, was examined using an electroencephalogram (EEG). The result showed that OCAM helped learners to understand the content being presented according to their aptitude scores, thus improving their brain activation. Findings from this study can be used to inform online system designers and developers about the importance of incorporating aptitude scores for customizing the representation of learning materials in an online environment.

Keywords Adaptive systems · Computer-mediated environment · Aptitude · Higher education

1 Introduction

The demand for providing effective mechanisms to aid learning in online adaptive systems has increased lately. Current research on adaptive learning has long been driven by pre-defined characteristics that represent individuals' mental model for undertaking certain learning activities (Al-Samarraie and Ahmad 2016; Stern and

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Woolf 2000). For instance, learners' state of engagement and motivation has been extensively utilized as the criterion in the design of current adaptive systems (Cocea and Weibelzahl 2007; Ross et al. 2018). Typically, this 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 their cognitive capacities of their mental model to undertake a certain behavior (Kandler et al. 2016). These differences may potentially contribute to information processing demands and, ultimately, behavior (Al-Samarraie et al. 2017; Becker 2005). In addition, the tendency to actively engage in a learning activity is somehow associated with one's ability to cognitively engage in the learning process without being distracted by other stimuli (Grand et al. 2016).

While adaptive learning systems have tended to customize the learning content in accordance with different learner characteristics (Truong 2016), the current focus has shifted toward behavioral contexts. Furthermore, current adaptive systems provide an attractive environment for implementing some basic forms of learner-centered adaptive learning, they are not without limitations. For example, the design of these systems is carried out with the aid of certain psychological traits that are usually assessed, only, at the beginning of the learning task (Al-Omari et al. 2016; Hsu et al. 2013; Hwang et al. 2012). One reason for this is that there seems to be a lack in continuous adaptation strategies for regulating the complexity of the representation in order to fit learners' cognitive demands (Highsmith 2013).

In addition, it can be assumed that the customization of a learning environment to deliver learning content based on the cognitive state of learners may not necessarily aid positive learning experience. It is evident that online learners who pose a higher level of learning ability may prefer to engage in much more complex learning activities, while those who pose a lower level of learning ability may do better with easier problems first (Holland 2006). In online learning environments, learners may continually experience changes in their cognitive demands when progressing in a task. In this regard, it is anticipated that the design of learning systems lacks the cognitive strategies required for regulating the complexity of learning content continuously. This is due to the limited knowledge about the cognitive components needed to formulate better adaptive strategies for these systems.

In computer-based learning environments, Sterman et al. (1996) highlighted the possible relationship between the use of dual-task design on cognitive activation with different levels of difficulty. Siegle et al. (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. Thus, inferring the cognitive state of students in procedural learning of online tasks could provide affective mediation for enhanced performance, through which cognitive aptitude can be used to regulate the learning resources needed to understand the learning topic. Such a state can be predicted based on the aptitude level of a person when learning the task, Snow (1992) referred to aptitude as one's readiness to undertake a learning task. Snow demonstrated how the interaction of person in a given situation is essential in indicating the initial states that influence later development. This study therefore 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 scores/levels. The present study aimed to contribute to the knowledge on how learners with definite cognitive abilities can be supported in particular learning tasks. This includes examining the interaction between the cognitive processing demands of programming task and the learners' current state of cognitive aptitude. The rest of this paper was organized in the following manner: Section 2, presents the system design. Section 3 gives the methodology of this study. Section 4 demonstrates results from the electroencephalogram (EEG) analysis. Section 5 discusses the research findings. Section 6 discusses the study's implications. Finally, Section 7 addresses limitations and possible future directions.

2 System design

Our review of the literature showed that learner may find themselves unable to continuously progress in a complex learning session due to the misfit between their skills and the given task (Hamilton and Cherniavsky 2006; Linder and Rochon 2003). Recently, many studies have attempted to examine several techniques for improving individual cognition during online learning. For instance, Guzdial (2015) addressed the difficulties in learning Computer Science subjects due to the complexity of the learning sequence, including the amount of information presented to the learner. Moons and De Backer (2013) attributed some of these difficulties to the lack of effective tools for maintaining individual cognitive load experience. Taraban et al. (2007), on the other hand, emphasized on the current lack of research to enrich procedural learning scenarios offered to online learners in their early learning stages. These learning challenges can be due 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, this study aimed at examining the impact of customizing online learning resources continuously across multiple learning sessions, based on the changes in learners' cognitive aptitude.

In this study, learners' cognitive state in terms of aptitude was treated as an indicator of learners' cognitive abilities that can be assessed through multiple progressive examinations of their skills in relation to the upcoming task. It was assumed that the progressive examination of the aptitude level of learners would help to continuously adjust the complexity of the learning resources, which is necessary for improving their brain activity while learning.

The presentation of learning materials in the one session was designed to explain substantial parts of the task. This means that the learning materials were designed to expand understandings of the task at hand, across learning sessions. For example, when a learner engages in a learning task of four sessions, an aptitude test was administrated to them after he/she complete each learning level of each session.

The examination of aptitudes may include aspects related to individual's knowledge, attitudes, cognitive abilities, skills, etc. (Regian et al. 2013). More recently, studies devoted to the design of learning systems based on the processing capacity of a person have addressed the influencing role of aptitude in interpreting the volume of information needed to be processed. We followed the guidelines of Koper and Tattersall (2005) for developing the online continuous adaptation mechanism (OCAM). It consists of three major models on the learner, assessment, and instruction.

2.1 The learner model

The learner model contains information that is usually gathered in between the learning sessions of each task. The supplied information is translated into learning scenarios that comply with certain needs. Studies devoted to the design of learning systems based on the processing capacity of a person have addressed the influencing role of aptitude in interpreting the volume of information needed to be processed (Kiss and Nikolov 2005). Examining students' aptitude level in a programming subject is essential for developing computer programming skills (Altintas et al. 2016; Barlow-Jones and van der Westhuizen 2017; Lambert 2015). However, most aptitude tests available in the literature are used to assess students' abilities to learn programming at the beginning of the course.

Here, the decision for configuring the representation of the learning scenario was typically based on one's prior knowledge about the topic. Precisely, we examined learners' aptitude level while progressing in a task, which is then used to decide the complexity of the upcoming learning session continuously. This was achieved by asking students to answer a series of multiple-choice questions. The test questions were designed to assess the degree of individual student readiness to learn the upcoming material. Two lecturers, with 5 years of experience in teaching programming, were asked to validate each test item. Here, the percentage for estimating the aptitude level was based on the accumulation of different items (high, average, and low). The content of the next learning task was then determined based on this classification.

2.2 The assessment model

Assessing learners' skills in a complex learning setting requires a structured scenario where the learning elements must be presented in a sequenced manner in order to comply with the learning goals (Al-Samarraie et al. 2013). The learning materials were related to the Java programming curriculum for a university study. In this study, we considered the use of domain-independent information measures to provide the system with clues about the learners' state of aptitude that is necessary for regulating the complexity of learning resources across all learning sessions. This was achieved by asking learners' a set of questions related to the upcoming task. A series of aptitude multiple choice items consisting of a problem was given to the learners before every learning session starts. These items were used to estimate the learners' aptitude level based on total score obtained on each item. The items for each test were adapted from well-known sources related to the learning topic. In addition, two lecturers were asked to identify the validity of each test item for assessing the total aptitude score of the learner. The percentage for estimating the aptitude level was based on the accumulation of different items (high, average, and low). The content of the next learning task is then determined based on this classification.

Previous reviews of the literature (e.g., Al-Samarraie et al. 2016; Blaschke 2012; Clark and Mayer 2011; Garrison 2011) declared that fostering online learners can be achieved by embedding different sorts of examples and external resources, meaning that learners with high cognitive load can be guided to understand the idea behind the learning task by using simple examples. Previous studies stated that embedding different sorts of resources may also hinder the learning process (Dolmans et al. 2005). Therefore, we considered categorizing the learners' aptitude scores as low, average, and high. These categories are commonly used in most online adaptive systems. However, it has different roles in assessing the level of learners in an online adaptive system. These roles were customized based on the previous works (Greene and Miller 1996; Kanfer and Ackerman 1989; Snow 1989, 1992) related to enhancing the cognitive aptitude of a person. In addition, structural differences in the brains of high and low aptitude users can be identified and that these features not only differ between the groups of high and low aptitude users, but are strongly correlated with individual Brain-computer interface (BCI) aptitude (Halder et al. 2013). Söderlind and Geschwind (2017) stated that aptitude test score may predict individuals' achievement in performing specific task. For this test to be a good predictor of individual students' performance, the test should be made with the consideration of particular learning materials; additionally, the test should successfully probe the ability an individual need to perform well at a given task.

In order to confirm the assumptions derived from the literature for determining the type of learning resources for each level, we examined the relationship between learners' cognitive state and type of learning resources using an EEG device. A total of 74 learners were used for this purpose. All learners took multiple cognitive aptitude tests to estimate their scores. Based on the recommendations of previous studies (Beckerman and Good 1981; Swanson 1990), test scores <49 were considered low, those from 50 to 69 were considered average, and those >70 were considered high. The EEG result showed that low-aptitude learners (n: 11) tended to experience high cognitive functioning (based on the activation of a particular brain region). The learners were asked about the nature of the representation of objects. Majority of the participants stated that there were limited clarifications and examples about the concept, which left them wondering about the nature of the task. In contrast, the learners with high aptitude level (n: 7) tended to experience low cognitive functioning, which was attributed by the learners to the high volume of information that pushed them to skip some parts in order to understand the overall concept. Learners with an average aptitude level (n: 8), however, found the learning content to be less appealing but acceptable. They also asserted that a piece of code can be embedded within the description. Based on these assertions, we were able to tailor the presentation of learning resources in the proposed system.

2.3 The instructional model

Based on the findings of previous studies (e.g., Goldberg et al. 2012; Park, O.-C., and Lee, J. 2003; Shute and Towle 2003; Towle and Halm 2005), knowledge that can be obtained from following a certain learning scenario can be facilitated by breaking the task into multiple phases instead of presenting it as a whole. For example, Goldberg et al. (2012) stated that the pedagogical model in any adaptive system should consists of two elements: user and domain. These elements are commonly used to develop recommended strategies where instruction can be modified with respect to the micro-adaptive approach. As such, guidance and feedback within a problem space can be triggered through specific actions taken in the system. Towle and Halm (2005) concluded that the differing levels of involvement and commitment among learners may require differing levels of encouragement and affirmation. For instance, learners with a low level of interest in the learning task may need substantial encouragement and guidance in order for them to continue with the learning process. The type of encouragement can be provided in the form of a representation strategy where the feedback a learner receives is tailored to their learning orientation. In this regard, the learning task must include a realistic level of elements to allow the system to regulate the complexity of activities by promoting abstraction and reflection. Here, we isolated the learning task into multiple sessions to progressively direct learners throughout the learning process. Figure 1 shows the process of the proposed OCAM based on progress in learners' cognitive aptitude. Such a system was assumed to empower the current learning practices of online adaptation for sustaining learners' brain activation. Figure 1 shows the presentation of learning contents for the three aptitude profiles. From the figure, it can be seen that the presentation of the content was different for each aptitude level. For example, learners scored higher on the aptitude test (presented after each learning level of each session) will be directed to a complex learning situation. This includes guiding learners through an abstract learning experience that contains a brief explanation about the concept being learned. In addition, learners scored an average on the aptitude test

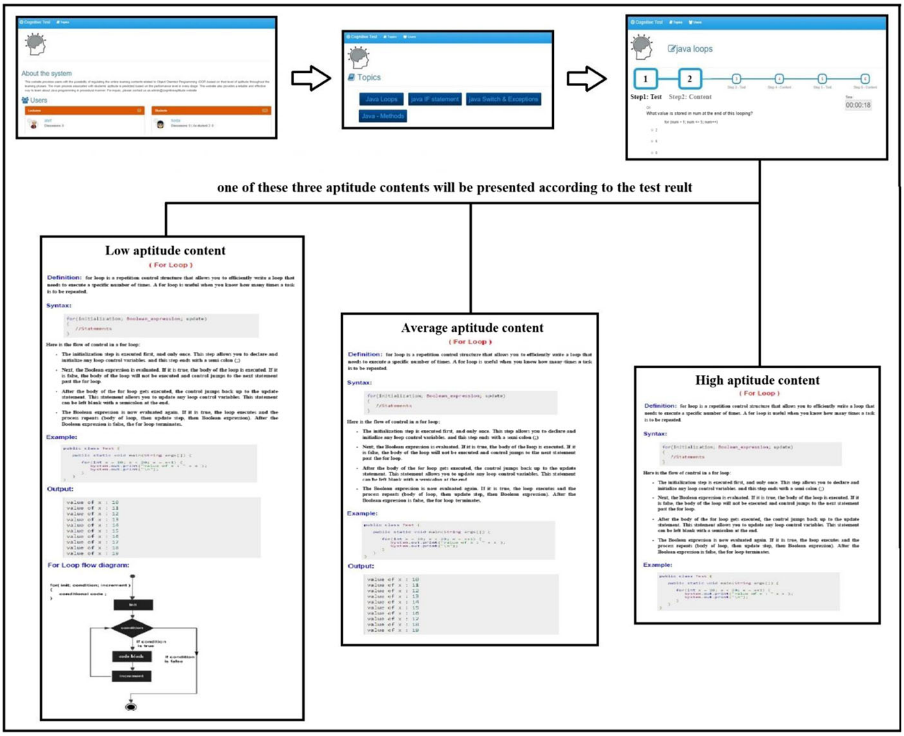


Fig. 1 OCAM content representation for each aptitude profile

will be provided with visual guides such as diagrams and textual annotations into the presentation. Finally, learners scored low on the aptitude test will be guided toward more explanation supported with examples.

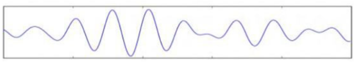
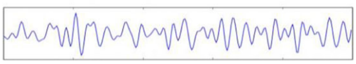
The learning materials used in this study were about Java programming. Two university lecturers were asked to provide learning materials about certain topics that they are going to teach at the classroom. These materials were uploaded to the system and students from the same classroom were identified to participate. They were asked to learn the provided materials with the proposed OCAM prior to the classroom session. The presentation of learning materials in the one session was designed to explain substantial parts of the task. This means that the learning materials were designed to expand understandings of the task at hand, across learning sessions.

3 Method

A total of 12 participants were selected using purposive sampling for piloting. The participants were different from the one we used in the design phase. The selection of the participants was based on their interest in participating in the study. The EEG data was collected from all the participants (second year students). The EEG is typically a non-invasive method that is commonly used to record and interpret the ongoing electrical activity in the brain along the scalp. The process involves recording the electronic signals produced when brain cells (known as called impulses) communicate with each other. The sensors record the ongoing activities (real-time) by placing them at special areas on the scalp. Brain activities are interpreted based on its rhythms in which the activities associated with each rhythm are presented from the perspective of the individual's mental states and conditions. Thee rhythms of Theta, Alpha, and Beta were used in this study (see Table 1).

A total of 7 students were male and only 5 students were female. The participants' age ranged from 20 to 25 years. Participants were instructed to undertake three learning tasks related to java programming. The participants received a research credit in exchange for their participation.

Table 1 Brain activity rhythms

Brainwave Type	Frequency range	Mental states and conditions	Illustration
Theta (θ)	4.0 Hz to 7.0 Hz	A person who has taken time off from a task.	
Alpha (α)	8.0 Hz to 12 Hz	A person who has completed a task.	
Beta (β)	12 Hz to 30 Hz	A person engaging in a task.	

3.1 Ethics statement

This work was reviewed and approved by the ethics committee in our university and informed consent was obtained from the participants before the study began.

3.2 EEG configuration

In this study, we used Epoc Emotiv, which is a computer interface EEG tool that includes 16 electrodes. These electrodes were placed directly onto the students' scalp (see Fig. 2). It contains a two-axis gyroscope that is commonly used to read head movements through space. The main advantage of this tool is that it can interpret students' facial expressions, head rotation, and emotional state, and can map up to 13 different thoughts as input through a USB to a connected PC.

Figure 2 shows the emotive channels used in this study. It contains 14 channels (labeled as AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) with 2 reference channels. The channel notation is based on the location on the scalp; even numbers represent the channels on the right side while odd numbers indicate those on the left side:

- Channel AF3, AF4, F3 and F4, F7, and F8: These channels are located at the Frontal area of the scalp, as denoted by the letter F, and they record activities related to attention, judgment, motor planning, verbal expression, and emotional expression, respectively.
- Channel FC5 and FC6: These channels are located at the Fronto-Cenral area of the scalp and they record activities related to the right body controller and left body controller, respectively.

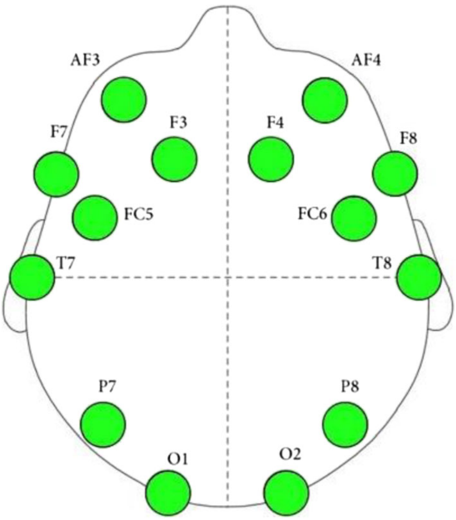


Fig. 2 Electrodes placement in EEG

- Channel T7 and T8: These channels are located at the temporal side of the scalp, represented by the letter "T." These channels are used to record activities related to verbal and emotional memory, respectively.
- Channel P7 and P8: These channels are located at the Parietal side of the scalp, denoted by the letter "P." These channels are used to record activities related to verbal understanding, emotional understanding, and motivation.
- Channel O1 and O2: These channels are located at the Occipital side of the scalp, denoted by the letter "O." The researcher used these channels to infer students' visual processing.

Independent component analysis was used to isolate the independent sources that are linearly mixed in several sensors, which helped in identifying the unwanted artefacts from the original signals, such as muscle activity, eye blinks, and electrical noise.

3.3 Procedure

Upon arriving at the computer lab, the participants were instructed to use the proposed system that regulated the presentation of the content according to their level of cognitive aptitude in all learning sessions. The students were asked to use the system for 20 min, to learn about one programming task (consists of three learning sessions). Prior to the extraction of EEG data, we allowed the activation of the students' brain through one learning task. The main reason of doing so was to ensure students' familiarity with the system and to eliminate any possible anxiety while using the system for the first time. Additionally, it offered better chances of explaining the students' brain activation after spending some time in attaining the learning objective (Bong 2001). After finishing the EEG session, the data for each participant was labeled and stored for future analysis.

4 Results

Figure 3 shows the participants' averaged power for frequency bands of theta, alpha and beta. The EEG signals were recorded for each participant in a rest-state activity and in a learning activity (three sessions). It can be noted that participants' brain activation when learning with OCAM had significantly influenced their learning performance. For example, the theta power band represents the performance of learners' brain activation when experiencing learning sessions customized based on their aptitude scores. An increase in the theta band power is usually reasoned to the increase in task difficulty and cognitive load. In contrast, the alpha power decreased when the task difficulty and cognitive load of the person increased (Pfurtscheller et al. 2005). The alpha band power was gradually increasing when participants progress in the learning task. Finally, the beta power band was investigated to estimate how OCAM can stimulate students' level of consciousness and their engagement with the task. In this regard, a gradual increment in the participants' beta band power was observed, which indicate that learners were experiencing an improvement in their level of engagement (Freeman et al. 1999). In the rest state, the baseline input translates into weak-intensity feedback interactions with other intermediate networks, causing low alpha activity (learning tasks) and a high rest rate.

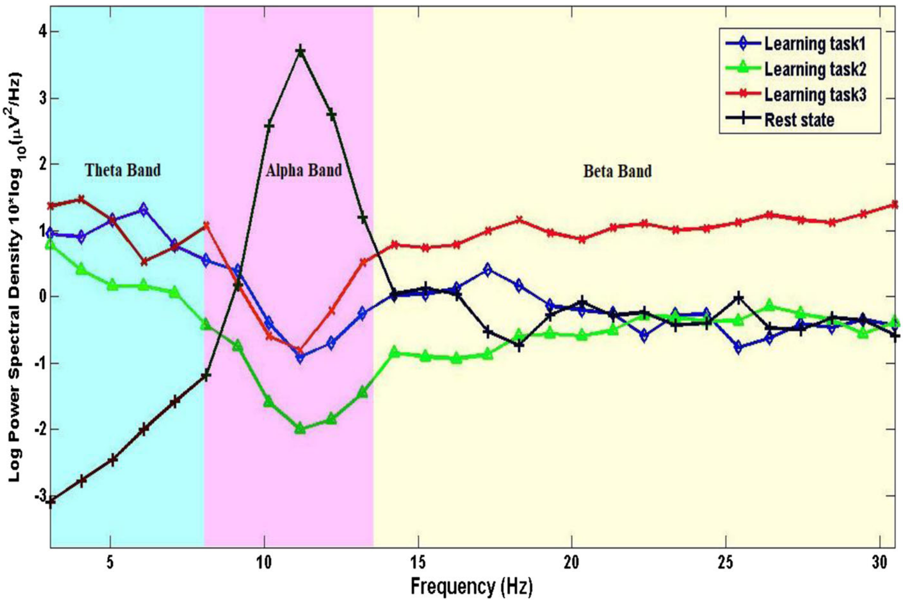


Fig. 3 Power frequency for each learning session (Log power spectral density refers to the spectral energy distribution that would be found per unit time; frequency (Hz) refers to the activation in a specific interval of time)

The above-mentioned results were also supported by the learners' brain spectrum topography in the three learning sessions (see Fig. 4). From the figure, it can be noted that all the participants experienced, gradually, higher alpha band activation [first session (M = 0.82, SD = 0.23), second session (M = 0.64, SD = 0.09), and third session (M = 0.90, SD = 0.05)]. It can be observed that alpha band power was relatively higher in the third learning session which indicate that leaners' activation has improved with the use of OCAM. In contrast, the result also showed an increment in the theta band power [first session (M = 1.86, SD = 1.27), second session (M = 0.97, SD = 0.27), and third session (M = 2.36, SD = 1.21). The beta power level was also increasing [first session (M = 0.38, SD = 0.33), second session (M = 0.31, SD = 0.22), and third session (M = 0.46, SD = 0.16)]. It is anticipated that students' brain activation (resulting from the gradual increment of alpha, theta, and beta-band powers) was higher in the third learning session.

5 Discussion

The design of current adaptive systems consists of certain functionalities for configuring the learning environment based on an initial examination of certain cognitive aspects (such as personality, attention, cognitive load, etc.) (Buckley 2008). These systems are inadequate in that the representation is not continuously regulated in accordance with the learners' cognitive levels. Therefore, it was assumed that by regulating the representation of learning content continuously learners will be able to process the learning contents more actively. We demonstrated an effective online learning solution by looking at the role of students' aptitude profile in regulating the complexity of the learning contents in relation to their ability to undertake specific

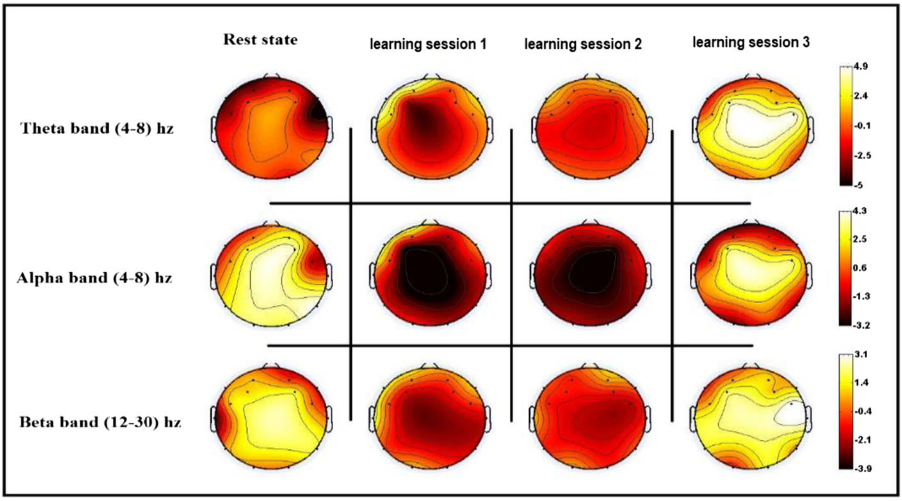


Fig. 4 Brain activation of different frequency bands at each learning session

tasks. We also validated the aptitude roles (high, medium, and low) among 12 students using EEG technology. The findings showed that students' cognitive states (based on reading from Theta, Alpha, and Beta bands) were positively affected by the use of the system. Such affect may potentially enable the modulation of learners' cognitive engagement in an online context. This is evident in the work of Hamari et al. (2016) who demonstrated how variation in learning ability reflects different learning values via the increased engagement, particularly when learners perceive the environment to provide them with the facilitating elements to understand the materials presented to them. Since adjusting the complexity of the task has always been one of the prominent aims of syllabus designers (Soleimani and Rezazadeh 2013), accommodating the learning needs of high-and low-aptitude students can increase students' academic performance (Ironsmith and Eppler 2007). It was found that when the representation of a learning task is customized in accordance with the learners' cognitive aptitude, they will effectively progress through the learning process. This is in line with some studies (e.g., Frost and McCalla 2015; Georgouli 2002) that have established that the learning objects may vary based on the aptitude and motivational aspects of the student's behavior. This study anticipated that the OCAM would allow students to actively engage in the learning process by representing information within the cognitive domain of the individual learner. According to Rodríguez and Ayala (2012), the ability of presenting content according to the user needs can offer an appropriate support for a personalized learning experience. Therefore, it is reasonable to say that the increased students' brain activation can be attributed to their interaction with content that resemble their aptitude profile. It is believed that regulating the learning process at an individual level would increase individual control beliefs and achievement, especially when the generated learning materials are adapted to meet individual learner abilities to process information effectively (Yang et al. 2013). From a cognitive perspective, the students' brain activation in this study seems to be affected by the presentation of learning resources on a continuous manner, which might potentially influence their cognition and episodic memory continuums (Olson and Berryhill 2009). Finding from this study contributes to the concept of relational complexity theory by Halford et al. (1998) and regulatory fit theory of by Higgins (2005) in that by continuously linking the aptitude level of learners to the complexity of the learning material, we can eventually improve their overall learning experience.

6 Implications

A number of implications can be drawn from the findings of this study. This includes underling the process for developing online adaptive systems for learning and its impact on learners' behavioral and cognition dimensions. With limited studies on the role of aptitude profile in facilitating learning in an online environment, the present study provides evidence about the impact of cognitive aptitude in the design of online learning systems on learners' abilities to process information effectively. The result presented in this work 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 for regulating task complexity according to the learners' aptitude profile. This would help learners to meaningfully process the presented information and make inferences necessary for understanding the learning content. It is assumed that the proposed OCAM would promote engagement among online learners by increasing their interest about the learning content, which in turn would promote their participation. Our findings can be used to inform online system designers and developers about the importance of incorporating aptitude scores for customizing the representation of learning materials in an online environment. It also provides some useful evidence about the application of aptitude scores in predicting the level of challenge a learner needs to participate actively in the online learning process.

7 Limitations and future works

Despite this, some limitations should be considered in the future. For example, this study was limited to the role of learners' cognitive aptitude to learn about programming subject in which other subjects may involve different difficulties or demands for learners based on their level of experience and previous knowledge. In addition, the brain activation from using the OCAM was not compared with other traditional learning methods. Although the study sample was sufficient for an EEG study, it may be a limitation for other quantitative studies. Certain behavioral aspects, such as anxiety and confusion were not considered in this study due to the limited theoretical support and the technical requirements for assessing such states using EEGs. Therefore, future studies can be conducted to further explore the role of OCAM in facilitating students' learning of other subjects. An experimental study can also be carried out to assess differences in learners' learning performance when using OCAM and the traditional e-learning system. Also, other emotional and behavioral responses can be deeply investigated using an advanced EEG recording system and analysis technique.

Acknowledgements This study was supported by Research University Grant (No. 1001/PMEDIA/8016063) of Universiti Sains Malaysia.

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References

Al-Omari, M., Carter, J., & Chiclana, F. (2016). A hybrid approach for supporting adaptivity in e-learning environments. *The International Journal of Information and Learning Technology, 33*(5), 333–348.

Al-Samarraie, H., & Ahmad, Y. (2016). Use of design patterns according to hand dominance in a mobile user interface. *Journal of Educational Computing Research, 54*(6), 769–792.

Al-Samarraie, H., Teo, T., & Abbas, M. (2013). Can structured representation enhance students' thinking skills for better understanding of E-learning content? *Computers & Education, 69*, 463–473.

Al-Samarraie, H., Selim, H., & Zaqout, F. (2016). The effect of content representation design principles on users' intuitive beliefs and use of e-learning systems. *Interactive Learning Environments, 24*(8), 1758–1777.

Al-Samarraie, H., Selim, H., Teo, T., & Zaqout, F. (2017). Isolation and distinctiveness in the design of e-learning systems influence user preferences. *Interactive Learning Environments, 25*(4), 452–466.

Altintas, T., Gunes, A., & Sayan, H. (2016). A peer-assisted learning experience in computer programming language learning and developing computer programming skills. *Innovations in Education and Teaching International, 53*(3), 329–337.

Barlow-Jones, G., & van der Westhuizen, D. (2017). Problem solving as a predictor of programming performance. Paper presented at the Annual Conference of the Southern African Computer Lecturers' Association, Problem Solving as a Predictor of Programming Performance.

Becker, K. L. (2005). Individual and organisational unlearning: Directions for future research. *International Journal of Organisational Behaviour, 9*(7), 659–670.

Beckerman, T. M., & Good, T. L. (1981). The classroom ratio of high-and low-aptitude students and its effect on achievement. *American Educational Research Journal, 18*(3), 317–327.

Blaschke, L. M. (2012). Heutagogy and lifelong learning: A review of heutagogical practice and self-determined learning. *The International Review of Research in Open and Distributed Learning, 13*(1), 56–71.

Bong, M. (2001). Role of self-efficacy and task-value in predicting college students' course performance and future enrollment intentions. *Contemporary Educational Psychology, 26*(4), 553–570.

Buckley, W. (2008). Society as a complex adaptive system. *Emergence: Complexity and Organization, 10*(3), 86.

Clark, R. C., & Mayer, R. E. (2011). *E-learning and the science of instruction: Proven guidelines for consumers and designers of multimedia learning*. John Wiley & Sons.

Cocea, M., & Weibelzahl, S. (2007). Eliciting motivation knowledge from log files towards motivation diagnosis for adaptive systems. Paper presented at the International Conference on User Modeling, Eliciting Motivation Knowledge from Log Files Towards Motivation Diagnosis for Adaptive Systems.

Dolmans, D. H., De Grave, W., Wolfhagen, I. H., & Van Der Vleuten, C. P. (2005). Problem-based learning: Future challenges for educational practice and research. *Medical Education, 39*(7), 732–741.

Freeman, F. G., Mikulka, P. J., Prinzel, L. J., & Scerbo, M. W. (1999). Evaluation of an adaptive automation system using three EEG indices with a visual tracking task. *Biological Psychology, 50*(1), 61–76.

Frost, S., & McCalla, G. I. (2015). An approach to developing instructional planners for dynamic open-ended learning environments. Paper presented at the AIED Workshops.

Garrison, D. R. (2011). *E-learning in the 21st century: A framework for research and practice*. Taylor & Francis.

Georgouli, K. (2002). The design of a 'motivating'intelligent assessment system. Paper presented at the International Conference on Intelligent Tutoring Systems.

Goldberg, B., Brawner, K., Sottilare, R., Tarr, R., Billings, D. R., & Malone, N. (2012). *Use of evidence-based strategies to enhance the extensibility of adaptive tutoring technologies*. Paper presented at the Interservice/industry training, simulation, and education conference (I/ITSEC).

Grand, J. A., Braun, M. T., Kuljanin, G., Kozlowski, S. W., & Chao, G. T. (2016). The dynamics of team cognition: A process-oriented theory of knowledge emergence in teams. *Journal of Applied Psychology, 101*(10), 1353–1385.

Greene, B. A., & Miller, R. B. (1996). Influences on achievement: Goals, perceived ability, and cognitive engagement. *Contemporary Educational Psychology, 21*(2), 181–192.

Guzdial, M. (2015). What's the best way to teach computer science to beginners? *Communications of the ACM, 58*(2), 12–13.
Halder, S., Varkuti, B., Bogdan, M., Kübler, A., Rosenstiel, W., Sitaram, R., & Birbaumer, N. (2013). Prediction of brain-computer interface aptitude from individual brain structure. *Frontiers in Human Neuroscience, 7*, 105.
Halford, G. S., Wilson, W. H., & Phillips, S. (1998). Processing capacity defined by relational complexity: Implications for comparative, developmental, and cognitive psychology. *Behavioral and Brain Sciences, 21*(06), 803–831.
Hamari, J., Shernoff, D. J., Rowe, E., Coller, B., Asbell-Clarke, J., & Edwards, T. (2016). Challenging games help students learn: An empirical study on engagement, flow and immersion in game-based learning. *Computers in Human Behavior, 54*, 170–179.
Hamilton, E., & Cherniavsky, J. (2006). Issues in synchronous versus asynchronous elearning platforms. In H. F. O'Neil & R. S. Perez (Eds), *Web-based learning: Theory, research and practice.* Mahway:Erlbaum.
Higgins, E. T. (2005). Value from regulatory fit. *Current Directions in Psychological Science, 14*(4), 209–213.
Highsmith, J. (2013). *Adaptive software development: A collaborative approach to managing complex systems*. Addison-Wesley.
Holland, J. H. (2006). Studying complex adaptive systems. *Journal of Systems Science and Complexity, 19*(1), 1–8.
Hsu, C.-K., Hwang, G.-J., & Chang, C.-K. (2013). A personalized recommendation-based mobile learning approach to improving the reading performance of EFL students. *Computers & Education, 63*, 327–336.
Hwang, G.-J., Sung, H.-Y., Hung, C.-M., Huang, I., & Tsai, C.-C. (2012). Development of a personalized educational computer game based on students' learning styles. *Educational Technology Research and Development, 60*(4), 623–638.
Ironsmith, M., & Eppler, M. A. (2007). Faculty forum: Mastery learning benefits low-aptitude students. *Teaching of Psychology, 34*(1), 28–31.
Kandler, C., Riemann, R., Angleitner, A., Spinath, F. M., Borkenau, P., & Penke, L. (2016). The nature of creativity: The roles of genetic factors, personality traits, cognitive abilities, and environmental sources. *Journal of Personality and Social Psychology, 111*(2), 230–249.
Kanfer, R., & Ackerman, P. L. (1989). Motivation and cognitive abilities: An integrative/aptitude-treatment interaction approach to skill acquisition. *Journal of Applied Psychology, 74*(4), 657–690.
Kiss, C., & Nikolov, M. (2005). Developing, piloting, and validating an instrument to measure young learners' aptitude. *Language Learning, 55*(1), 99–150.
Koper, R., & Tattersall, C. (2005). Preface to learning design: A handbook on modelling and delivering networked education and training. *Journal of Interactive Media in Education, 2005*(1).
Lambert, L. (2015). Factors that predict success in CS1. *Journal of Computing Sciences in Colleges, 31*(2), 165–171.
Linder, U., & Rochon, R. (2003). Using chat to support collaborative learning: Quality assurance strategies to promote success. *Educational Media International, 40*(1–2), 75–90.
Moons, J., & De Backer, C. (2013). The design and pilot evaluation of an interactive learning environment for introductory programming influenced by cognitive load theory and constructivism. *Computers & Education, 60*(1), 368–384.
Olson, I. R., & Berryhill, M. (2009). Some surprising findings on the involvement of the parietal lobe in human memory. *Neurobiology of Learning and Memory, 91*(2), 155–165.
Park, O.-C., & Lee, J. (2003). Adaptive instructional systems. *Educational Technology Research and Development, 25*, 651–684.
Pfurtscheller, G., Neuper, C., Brunner, C., & Da Silva, F. L. (2005). Beta rebound after different types of motor imagery in man. *Neuroscience Letters, 378*(3), 156–159.
Regian, J. W., Shute, V. J., & Shute, V. (2013). *Cognitive approaches to automated instruction*. Routledge.
Rodríguez, V., & Ayala, G. (2012). Adaptivity and Adpatability of learning Object's Interface. *International Journal of Computer Applications, 37*(1), 6–13.
Ross, B., Chase, A.-M., Robbie, D., Oates, G., & Absalom, Y. (2018). Adaptive quizzes to increase motivation, engagement and learning outcomes in a first year accounting unit. *International Journal of Educational Technology in Higher Education, 15*(1), 30.
Shute, V., & Towle, B. (2003). Adaptive e-learning. *Educational Psychologist, 38*(2), 105–114.
Siegle, G. J., Ichikawa, N., & Steinhauer, S. (2008). Blink before and after you think: Blinks occur prior to and following cognitive load indexed by pupillary responses. *Psychophysiology, 45*(5), 679–687.
Snow, R. E. (1989). Toward assessment of cognitive and conative structures in learning. *Educational Researcher, 18*(9), 8–14.
Snow, R. E. (1992). Aptitude theory: Yesterday, today, and tomorrow. *Educational Psychologist, 27*(1), 5–32.

Söderlind, J., & Geschwind, L. (2017). More students of better quality? Effects of a mathematics and physics aptitude test on student performance. *European Journal of Engineering Education, 42*(4), 445–457.

Soleimani, H., & Rezazadeh, M. (2013). The effect of increase in task cognitive complexity on Iranian EFL learners' accuracy and linguistic complexity: A test of Robinson's cognition hypothesis. *Applied Research on English Language, 53*(12), 41.

Sterman, M. B., Kaiser, D. A., & Veigel, B. (1996). Spectral analysis of event-related EEG responses during short-term memory performance. *Brain Topography, 9*(1), 21–30.

Stern, M. K., & Woolf, B. P. (2000). Adaptive content in an online lecture system. Paper presented at the Adaptive hypermedia and adaptive Web-based systems, Adaptive Content in an Online Lecture System.

Swanson, H. L. (1990). Influence of metacognitive knowledge and aptitude on problem solving. *Journal of Educational Psychology, 82*(2), 306–314.

Taraban, R., Anderson, E. E., DeFinis, A., Brown, A. G., Weigold, A., & Sharma, M. (2007). First steps in understanding engineering students' growth of conceptual and procedural knowledge in an interactive learning context. *Journal of Engineering Education, 96*(1), 57–68.

Towle, B., & Halm, M. (2005). *Designing adaptive learning environments with learning design Learning design* (pp. 215–226). Springer.

Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. *Computers in Human Behavior, 55*, 1185–1193.

Yang, T.-C., Hwang, G.-J., & Yang, S. J.-H. (2013). Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles. *Journal of Educational Technology & Society, 16*(4), 185–200.