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An experimental study on an adaptive e-learning environment based on learner's personality and emotion

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Abstract

E-learning enables learners to learn everywhere and at any time but this kind of learning lacks the necessary attractiveness. Therefore, adaptation is becoming increasingly important and the recent research interest in the adaptive e-learning system. Since emotions and personality are important parts of human characteristics, and they play a significant role in parts of adaptive e-learning systems, it is essential to consider them in designing these systems. This paper presents an empirical study on the impact of using an adaptive e-learning environment based on learner's personality and emotion. This adaptive e-learning environment uses the Myers-Briggs Type Indicator (MBTI) model for personality and the Ortony, Clore & Collins (OCC) model for emotion modeling. The adaptive e-learning environment is compared with a simple e-learning environment. The results show that students deal with the adaptive e-learning environment (experimental group) gained high scores than others (control group). The rate of progress in quiz score of the experimental group is almost 4.6 times more than the control group. Also, the rate of hint use is decreased more among the experimental group rather than the control group because the level of their knowledge is increased through learning in an adaptive environment. Furthermore, the findings display that the control group tries more to answer the questions in post-quiz while the experimental group has a low effort. Finally, the students expressed the adaptive e-learning environment is more attractive and close to their personality traits. Moreover, it can understand their emotional state better, has a suitable reaction to them, and improves their learning rate.

Keywords Adaptive e-learning · Personality · Emotion · MBTI · OCC

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1 Introduction

Nowadays, access to the web has provided new opportunities in education. The number of e-learning systems and online degree programs has considerably increased in the new century (Allen and Seaman 2007). Despite the increase in using e-learning systems and their advantages such as the development of transferable learner's skills like collaboration, communication, and problem-solving, access to different online resources, and self-directed learning, learning e-learning systems suffer from several problems. The most important problem of these systems is high dropout rate (Yukselturk et al. 2014). A lot of learners are easily leaving e-learning systems without satisfaction (Carr 2000; Inan et al. 2009; Kotsiantis et al. 2003; Lykourentzou et al. 2009; Willging and Johnson 2009). This is due to the fact that this type of learning environment cannot interact with learners as well as traditional learning environments. In other words, it is essential to consider the human characteristics and use them in the design and implementation of e-learning environments, aiming to make them more realistic and attractive (Niesler and Wydmuch 2009).

Today, the research in the field of adaptive e-learning systems has received more attention universally (Mustafa and Sharif 2011). An adaptive e-learning system is a system that produces the most suitable behavior to interact for each particular learner. The aim of this system is improving the individual learning process (Weber 1999; De Bra et al. 2004; Henze and Nejdl 2004). Since emotions and personality are important parts of human characteristics, and they play a significant role in parts of adaptive systems such as implicit feedback, it is necessary and must be considered in designing adaptive learning systems. Numerous adaptive e-learning systems have been developed to consider human characteristics but most of these systems just consider emotions, mood, learning styles, motivations, or personality alone (Trantafillou et al. 2002; Grigoriadou et al. 2001; Wolf 2003; Bajraktarevic et al. 2003). There is a few research used combination some of the human characteristics together (Conati and Zhou 2002; Chalfoun et al. 2006; Fatahi et al. 2009; Fatahi and Moradi 2016). In addition, there is a few research used combination some of the human characteristics together (Conati and Zhou 2002; Chalfoun et al. 2006; Fatahi et al. 2009; Fatahi and Moradi 2016). In addition, most of the research in adaptive e-learning system area does not pay attention to the experimental evaluation of impact these systems have had on learners.

In this study, we have designed and implemented two versions of e-learning systems. One of them is a simple e-learning environment and the other one is an adaptive e-learning environment based on learner's personality and emotion. The goal of this paper is the evaluation of impact the adaptive e-learning environment which uses learner's personality and emotion to interact with the learner.

2 Background

This section includes two part, first, psychological principles, which used in this study, is explained. The second part is about several important research had been done in the area.

2.1 Psychological principles

Psychologists have presented a various definition of emotion. Darwin (1998) considered emotions to represent mechanisms for the adaptation and survival of the individual. He identified seven groups that include over thirty different emotions. James (1890) defined emotion as a feeling of the 'bodily expressions' which follow the perception of an 'exciting fact'. He identified 'coarser' (grief, fear, rage, and love) and 'subtler' emotions 'whose organic reverberation is less obvious and strong'. On the other hand, clinical studies of the brain have shown that emotion is associated with complex biological processes. All of the various definition of emotion demonstrates emotion is a complex phenomenon.

Many studies have supported that emotion affect reasoning, decision-making, working memory, memorizing, and learning (Blanchette and Richards 2010; Paulus and Angela 2012; Osaka et al. 2013). Also, these studies have revealed that the learner's emotional state impacts his performance then it should be considered in learner modeling (Kim and Pekrun 2014). Thus, many psychological models for emotion modeling in computer science have been proposed (Marsella et al. 2010; Rodríguez et al. 2011). One of the most famous of these models is the OCC model (Ortony et al. 1988). This model distinguishes 22 emotion types in three groups which are a consequence of events, actions of people, and aspects of objects. The first group of emotions includes emotions which are consequences of the events that have happened. These consequences are obtained according to the desirability or undesirability level of the events and the person's goals. The OCC model calculates the intensity of emotions based on a set of variables which are divided into two groups: global and local. One of the most important variables to calculate the first group of emotions is desirability. In this study, we are used the OCC model for emotion module of an adaptive e-learning system and our focus is on the desirability variable and its relationship with personality dimensions (Fatahi and Moradi 2016).

On the other hand, among the various attempts to understand and define personality, a number of definitions can be known. Schultz and Schultz (2016) defined personality as the external and internal aspects of individual features that affect the human behaviors in different situations. Hartmann (2006) believes that personality includes thoughts, feelings, desires and behavioral tendencies that exist in every person. Jung believed that there are three dimensions of personality which are Extroversion/Introversion (E/I); Sensing/Intuition (S/N); and Thinking/Feeling (T/F). Later, Myers and Briggs (Schultz and Schultz 2016) added a fourth dimension to this category Judging/Perceiving (J/P). According to the Center for Applications of Psychological Type, MBTI is the most universally used personality questionnaire; approximately 2,000,000 persons use MBTI for their personality detection every year. Moreover, the validity of the MBTI model has been widely identified (Kim et al. 2013) (Fatahi et al. 2016). MBTI is based on four two-dimensional functions which make sixteen personality types result from mixing the extremes of the four dimensions (Fig. 1). For example, individuals in the ISTP group are Introvert, Sensing, Thinking, and Perceiving. In this study, we are used MBTI model for personality module of adaptive e-Learning system.

Fig. 1 MBTI dimensions and MBTI types

2.2 Related works

Numerous studies have been carried out in the adaptive e-learning systems area, in this section; the most important ones are listed.

El Bachari et al. (2010) proposed LearnFit which is an adaptive e-learning model based on learners' personality. LearnFit is able to provide the system's teaching style based on a learner's preference in the e-learning environment. Bachari, et al. developed modules to determine a learner's learning preferences and to select a suitable teaching strategy for learners. The results demonstrated that teaching the learner according to learner's preference in e-learning education leads to progress in the learning process and would make the e-learning environment more enjoyable. It should be mentioned the personality model is used in this study was MBTI model. Wang and Liao (2011) focused on learners' characteristics, such as gender, personality types (introverted, mildly introverted, neutral, mildly extroverted, and extroverted), and anxiety levels (low, moderate, and high anxiety) to design an adaptive e-learning system. The adaptive e-learning system implemented to teach the English language. This system presents different levels of teaching content for grammar, vocabulary, and reading for learners with different combinations of characteristics. The results indicate that this adaptive e-learning system has a positive impact on student learning outcomes. The authors compared the results of their system with a simple e-learning system. The results show that learning performance in the adaptive e-learning system is significantly higher than a regular e-learning system. Kim et al. (2013) examined the relationship between a learner's personality dimensions and the influence of personality dimensions on learners' preferences. The findings of this research demonstrate individuals with different personality have different preferences and learning styles. Then, these differences should be considered in designing adaptive learning systems. The authors proposed design guidelines to provide appropriate material to learners based on their learning styles. Rani et al. (2015) suggested an ontology-driven system which is used to provide personalized learning materials for learners. To evaluate the system, a questionnaire which measures different dimensions such as learner, teacher, course, technology, and design is used. The findings show that the average score that was calculated for all dimensions is reasonable. Garcia-Cabot et al. (2015) carried out an empirical study on an adaptive mobile system. The goal of this research was evaluating the learning performance and attitude of learners when they use an adaptive mobile system. The results show that mobile learning adaptation had a limited effect on the learning performance of practical skills when compared to an e-learning system. The interesting result achieved about the practical assignments. The learners in the experimental group gained high score rather than control (e-learning) group in practical assignments. Also, learners express using mobile to learn materials are efficient, useful and easy to use. Bourkoukou et al. (2016) consider learner's personality to design a personalized e-learning system. The system works based on different learning scenario for each learner. It recommends appropriate learning materials according to the learner profile. Authors proposed an algorithm to recommend learning object to learners. After evaluating the proposed model, the findings illustrate the prediction accuracy of it is reasonable. Buckley and Doyle (2017) study the impact of learners' learning styles in a gamified learning environment. They believed gamification is used to increase learners' engagement, motivate and performance learning. The results of this research shows that individuals who have active or global learning styles have a positive impression of gamification. Also, the results indicate that learners who have a global learning style performed better the gamified learning activity. Alhathli et al. (2018) examines the impact of personality on the selection of next learning activities. The personality traits which considered are openness to experience (OE), emotional stability (ES) and self-esteem (SE) on the selection of learning activities. The authors found that considering learners' personality, and learning activity characteristics in an adaptive educational systems will enhance the learning experience and improve the quality of the learning activity selection.

Despite all these efforts, there is a lot of research in adaptive e-learning systems but there is no work on evaluating an adaptive e-learning system which considers personality and emotion of learner against a simple e-learning environment. In this paper, our aim is to compare an adaptive e-learning system which considers personality and emotion of learner and a simple learning environment.

3 Methodology

This study is based on an e-learning environment which includes many online courses. The course in this study is the "Introduction to computing systems and programming" (ICSP) which is taught to the first-year students at the school of electrical and computer engineering at the University of Tehran in Iran. Figure 2 displays the overview page of the course.

This research is designed in six steps.

Step 1: Determine the personality and goal of students

Since this study focuses on personality and emotion of learner as important human characteristics, then in the first step, the participants are asked to fill out the online MBTI questionnaire to determine their personality and become aware of their MBTI personality type. It should be noted that the participants may not pay enough attention to the questionnaire. Consequently, the questionnaires that are filled out quickly can be considered in this category. Furthermore, the questionnaires that are not filled out in a reasonable amount of time are also subject to being filled out carelessly. Thus, these questionnaires may be removed from the data collection. Therefore, in the first step, the personality of students based on MBTI is identified. Also, the goals of students are determined through a questionnaire is based on Ames's theory.

Step 2: Categorize students in experimental and control group

Since we found that the ISTJ group is the largest group of the sixteen MBTI personalities in the previous step, we categorize the students in two groups in the second step. One of them is an experimental group who will work with an adaptive e-learning system based on personality and emotion and a control group who will work with another version of the system without adaptation. In this study, the students who have.

ISTJ personality type belongs to the experimental group and participants who have other personality types are in the control group. Thus, in the second step, experimental and control group are identified.

Step 3: Pre-quiz

In this study, one of the chapters of the ICSP syllabus, "Pointers and Arrays" is selected to teach the students. In this step, the student logs in into the course page and have to participate in an online quiz consisting five questions about pointers and arrays which called Pre-quiz. This process helps us to measure the level of knowledge before learning materials and desirability level of him is associated with e-learning environment events.

Fig. 2 Overview page of the course

For each question of the quiz, the hint button is provided. If the student needs a hint to answer the question, use it easily. If the student clicks on a hint button and uses it, the system asks him how much the hint was helpful (Fig. 3). The student must give a rate on how much the hint was helpful. The rate is one to five, one means very low and five means very high.

Later, the student can go back to submit his answer to the question. After answering a question, the effort level of the student is asked (Fig. 4). This question determines how much the student had the effort to answer a question. The student should give a rate between one to five, one means very low and five means very high for the effort level. It should be mentioned that the time to answer each question is three minutes and after that, the system automatically redirects the student to the effort level measuring page.

Finally, the desirability level will be asked and the student should answer how much he desirable or undesirable of this learning environment event (Fig. 5). For example, it seems clear that the student could not answer questions has undesirable emotion.

Step 4: Teaching a subject

After the student answers all questions or skips them in Pre-quiz step, a part of the lesson on the subject “Pointers and Arrays” is taught to the student. It should be mentioned the designing e-learning environment for experimental and control group in the teaching section is totally different (Figs. 6 and 7).

For ISTJ individuals designing e-learning environment adapted to their personality dimensions and emotion. We explained how we designed an adaptive e-learning environment based on personality and emotion separately.

a) Adaptive e-learning environment based on personality

Fig. 3 Determine the helpfulness of the hint

Fig. 4 Determine the effort level

The ISTJ means Introversion, sensing, thinking and judging. These people learn best from an orderly sequence of details, likes to know the "right way" to solve problems, interested to learn structured.

materials, choose to work alone, likes quiet space to work, works on one thing for a long time, dislikes interruptions, prefer to begin with the details and facts, and then move towards concepts: there is also more liking for step-by-step exposition, likes logic, facts, and objectivity, sets up "shoulds" and "oughts" and regularly judges self against these (Dewar and Whittington 2000). In designing the adaptive e-learning system, we consider ISTJ individuals characteristics which are explained below:

Since ISTJ people choose to work alone and like quiet space to work, the online and personalized learning environment is fit with their preferences. Also, we added a progress bar to each page of the lesson so that the student knows how much he had the progress in the lesson. In addition, we highlighted current outlines in each page of the lesson. These features would help the ISTJ individuals who set up "shoulds" and "oughts" and regularly judges self against these. Since ISTJ people like fact and objective materials and they obtain information through their senses, not their intuitions, we used some pictures instead of text only. Furthermore, we added a navigation bar which shows topics and subtopics. It helps that the student knows what section will be present in the future and the student may want to change the flow of the lesson or skip some sections. Also, ISTJ persons need to know the goals and sub-goals of their task. Finally, due to ISTJ individuals prefer to work on one thing for a long time and dislike interruptions, this online learning course designed for 45 min.

b) Adaptive e-learning environment based on emotion

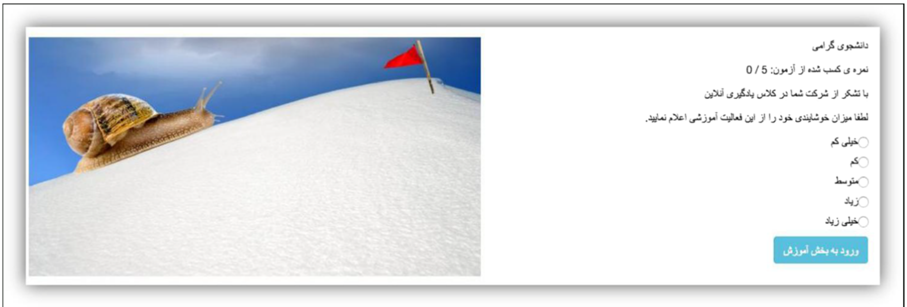

Fig. 5 Determine the desirability level

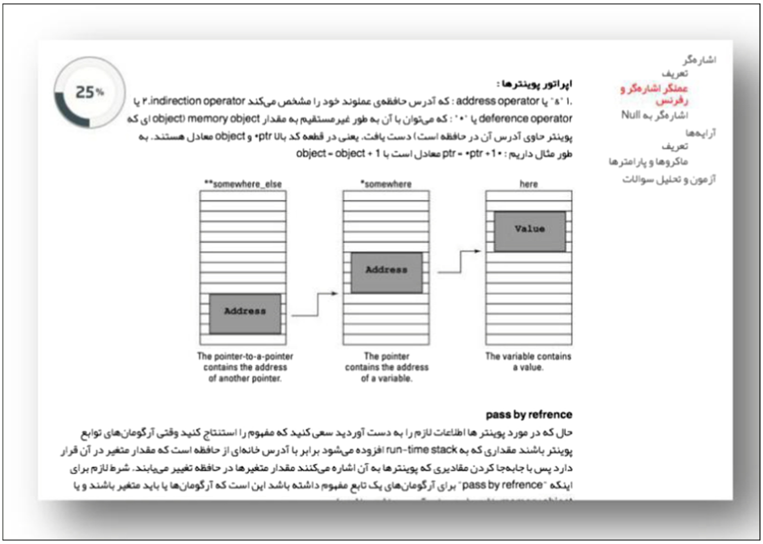

Fig. 6 Adaptive e-learning environment

As mentioned before, the OCC model is used in this study and we focus on desirability variable is one of the most important variables to calculate the first group of emotions. To calculate the desirability level, we used a computational model (Fatahi and Moradi 2016) which is based on learner's personality, eLearning environmental events, and learner's goals. The results show this model can predict desirability level 76% accuracy. Then, we used this model to predict student's desirability level. It should be mentioned

Fig. 7 Simple e-learning environment

we ask the desirability level of the student but we use the actual value for comparing with predict value of the model for sure.

After Pre-quiz and before starting the teaching, the desirability level of the student is determined.

After that, we used some motivational strategies to encourage the student to continue to work with the adaptive e-learning environment. These strategies are some encouraging message with energetic music, and animations.

Step 5: Post-quiz

After studying the lesson, students are tested with an online quiz consisting five questions about pointers and arrays which called Post-quiz. The process in the Pre-quiz and Post-quiz is same.

Step 6: Evaluating adaptive e-learning system

In the final step, all students in experimental and control group fill out a questionnaire consisting five questions about the impact of adaptive learning environment on the learning (Table 1).

The results of the comparison will be explained in the next section.

4 Experiment and results

We collected data from 222 students who enrolled in the course. Only 181 of students participated in the online MBTI questioner. The time the students spent on the MBTI questioner was recorded. As mentioned before, in order to minimize the error of data collection, students which spent less than three minutes and over eight minutes to fill the questioner was discarded. Eventually, 127 valid questioners were collected. Figure 8 shows the personality distribution of students in each dimension of MBTI and Fig. 9 shows the distribution of personality types of the MBTI.

As mentioned before, we consider two groups of students for experimental and control group. Based on the data collection phase, there are 27 students who have ISTJ personality type and just 16 of them participated in the online course and completed the

Table 1 Evaluation system questionnaire

Questions	Very low	Low	Medium	High	Very high
1- How much this e-learning environment is interesting?					
2- How much this e-learning environment close to the features of your personality?					
3- How much your emotional state understands?					
4- How much well the e-learning environment reacted to you (with the consideration of your emotional state)?					
5- How much this e-learning environment can be improved learning rate?					

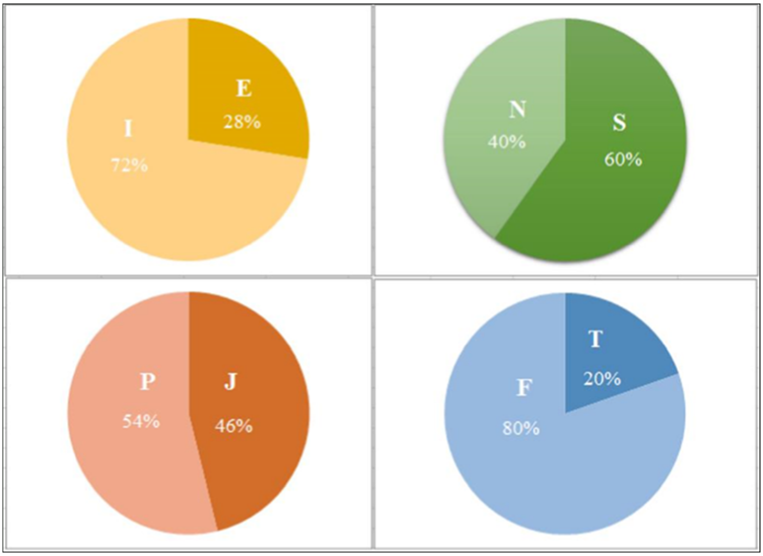

Fig. 8 The personality dimension distribution of students in each dimension of MBTI

course and answered the final questionnaire. Also, the number of other students which participated in the course and have others personality types were 100. Only 34 of them finished the Pre-quiz, only 29 of 34 finished the Post-quiz, and finally, 27 of them answered the final questioner. Therefore, there is 16 sample of ISTJ data (experimental group) and 27 of others personality type (control group). Since the number of data in the experimental and control group is not the same, we normalized the obtained results.

All results reported in two steps which are Pre-Quiz and Post-Quiz. In the Pre-quiz step, the students log in into the web course while they have not been trained. In the Post-Quiz, the students have been trained a subject. Figure 10 shows the scores that the experimental and control group of student obtained in Pre-quiz and Post-quiz. Figure 11 displays how much the student used the hint and Fig. 12 illustrates how much the hint was helpfulness. Furthermore, Fig. 13 shows the level of the student's effort to answer the quiz. Finally, Fig. 14, the desirability level of students is shown.

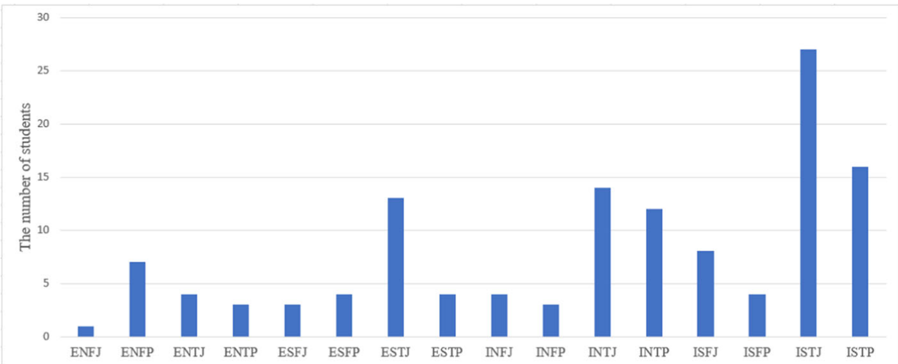

Fig. 9 The personality type distribution of students in each type of MBTI

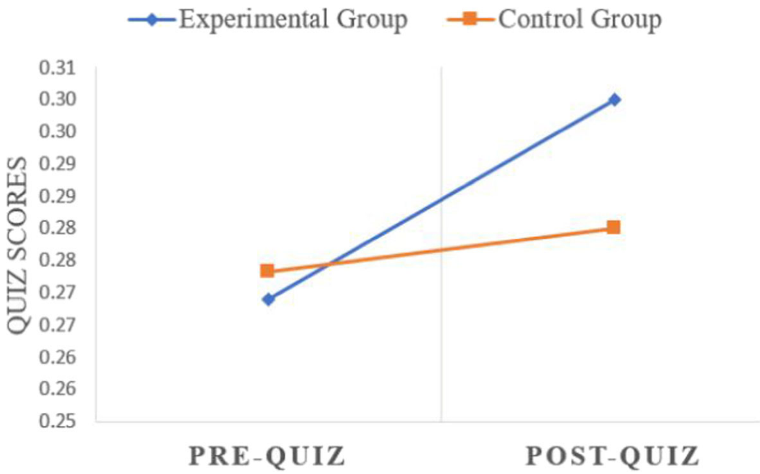

Fig. 10 Quiz scores

5 Discussions

The goal of this study is comparing a simple e-learning environment and an adaptive e-learning environment based on learner's personality and emotion. The results show that there are differences between these environments. As Fig. 10 shows, in the Pre-quiz, the control group gained higher scores in answering questions than the experimental group. It implies the level of knowledge about pointers and arrays is better among the control group. After teaching, the experimental group in the adaptive e-learning environment based on their personality and emotion improved their performance significantly rather than the control group. The rate of progress in quiz score of the experimental group is almost 4.6 times more than the control group.

The findings in Fig. 11 shows the rate of hint use is not the same between the experimental and control group in Pre-quiz and Post-quiz. In both groups, the rate of hint use is decreased that can be interpreted level of the knowledge of learners is increased so they do not need to use hints. The rate of hint use decreased 29.94%

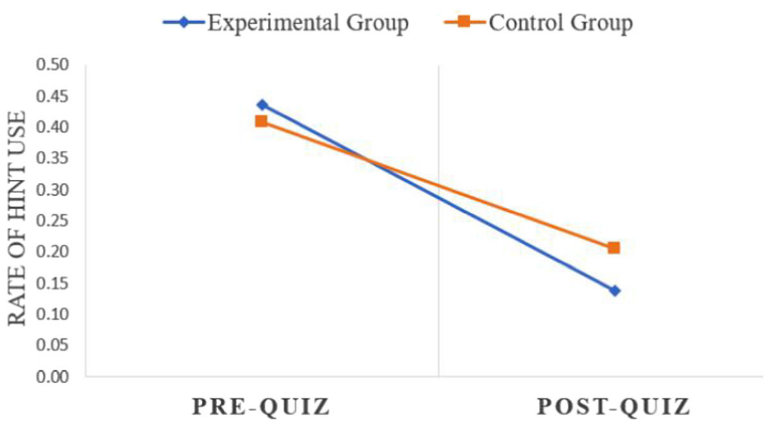

Fig. 11 The rate of hint use

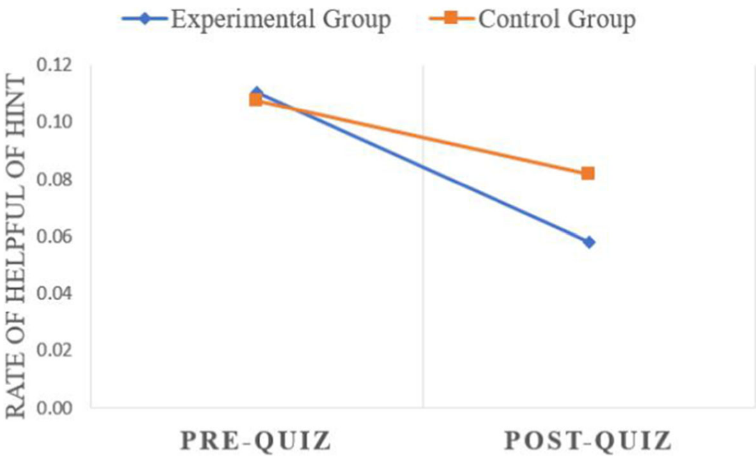

Fig. 12 The rate of helpful of hint

among the experimental group and 20. 23% among the control group that demonstrated much progress among the experimental group rather than the control group. The level of the knowledge of the experimental group is increased more than the control group so they use hint less. The results in Fig. 12 displays that the rate of helpful of the hint decreased among the two groups.

Decreasing the rate of helpful of hint among the experimental group is more than the control group. It may be the experimental group has a high expectation of an adaptive e-learning environment; therefore, the hints could not satisfy their expectations.

The effort level of the students in the two different environments is asked while they answer quizzes. Figure 13 shows that the control group tries more to answer the questions in post-quiz while the experimental group has a low effort. It also proves the results about quiz scores among two groups. The experimental group worked with an adaptive e-learning environment that causes improve their learning rate (Fig. 10).

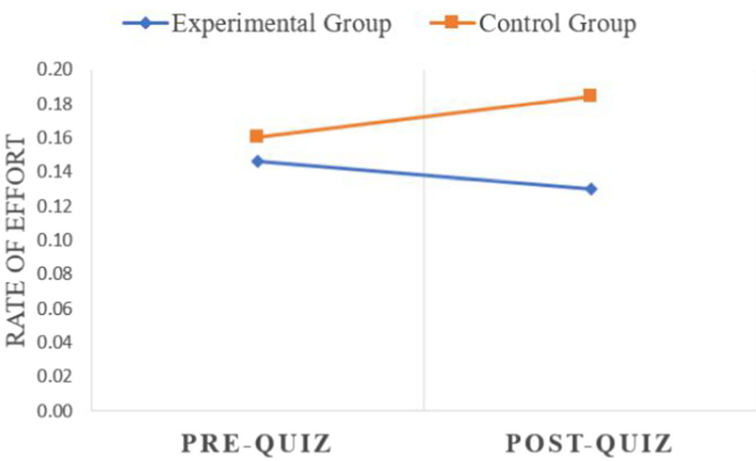

Fig. 13 The rate of effort

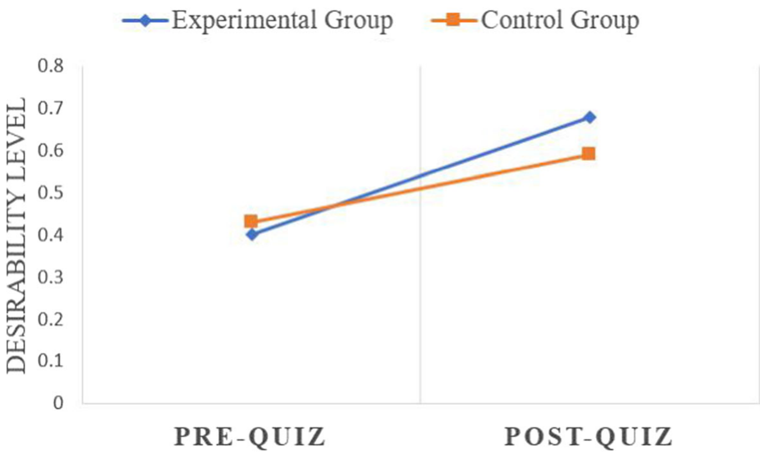

Fig. 14 The desirability level

When the students learn better their learning rate is improved and they have less effort to answer questions because the questions are easy for them.

Figure 14 display the desirability level which is increased among the two groups but there is not significant between experimental and control group. It is due to emotion features in designing the adaptive e-learning environment was weak and they could not make differences between the two groups. We should be considered more emotions features in designing adaptive learning environment.

Figure 15 shows the results of a questionnaire which filled out by two groups of students to compare two environments. As Fig. 15 display the adaptive e-learning system has more scores in all measures. The higher score is related to the appreciate reaction of the system which means how much the system has a suitable reaction after understanding learners' status. Also, the students confirm the adaptive learning was designed very close to their personality types.

6 Conclusion and future work

In this paper, an adaptive e-learning system based on personality and emotion designed, implemented and evaluated. We used the MBTI model for personality module and

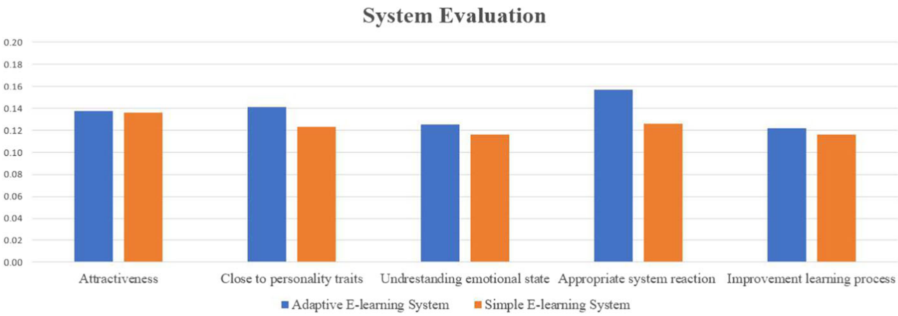

Fig. 15 The evaluation questionnaire results

OCC model for emotion module. The system tested in two versions for control and experimental group. The control group deals with a simple e-learning system while the experimental group interacts with an adaptive e-learning system based on personality and emotion. As the results have shown considering the human characteristics such as emotion and personality improves the learning process. The experimental group believed that the adaptive e-learning environment causes progress in their learning rate. Also, it can recognize their status in terms of emotional state and personality traits. Therefore, this system has fit strategies to interact with learners.

This finding can be used in later research in order to customize the e-learning environment. One limitation of this study was the number of participants in the course. In the future work, we can collect more data and designed the adaptive system for all sixteen personality types of the MBTI.

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