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Does Providing a Personalized Educational Game Based on Personality Matter? A Case Study

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ABSTRACT While researchers have highlighted the importance of considering learner's personality as a personalization parameter in computer based learning, very few studies have really addressed this parameter in educational games. Therefore, this paper presents an educational game which models learner's personality, specifically introvert/extrovert dimension, to serve as a personalized game learning environment. Fifty one learners were randomly assigned to a control and an experimental group which learned with a non-personalized and a personalized version of the game respectively. The experimental results show that the personalized educational game did not have a significant impact on learners' motivation, while it did significantly decrease learners' cognitive load. Besides, the learners who learned with the personalized version of the game revealed a significant higher degree of perceived usefulness and intention to use the game than those who learned with the non-personalized version of the game. The findings of this study can be used by educators and game designers to adopt and develop personalized game learning environments based on learner's personality.

INDEX TERMS Educational games, personalized learning, personality, computer based learning.

I. INTRODUCTION

Many researchers have recently focused on the development of educational games, given their positive effects on the learning process. However, when trying to motivate with educational games, an important problem might come from the fact that learners do not have the same educational needs, expectations and preferences [1], [2]. Therefore, in order to fulfil learners' individual differences, several researchers and practitioners have thought of using personalized learning systems instead of simply following the one size fits all approach [3]. Personalized learning systems can dynamically adjust the provided learning according to the preferences, abilities and knowledge of individual learner. They can also personalize instructions in order to enhance the learner's performance. Thus, various challenges found in traditional learning, such as the resources limitations, learner's motivation and diversity of learners' knowledge and preferred learning styles can be

addressed. This can help to decrease course drop-out rates, enhance learning outcomes and achieve learning goals [4]. It is therefore not surprising that advance personalized learning was identified by the National Academy of Engineering [5] as one of the 14 important challenges for engineering in the 21st Century.

Many personalization parameters are reported in the literature, which are used by various personalized learning systems. One of these parameters is "personality" which is widely identified as an important indicator of individual differences [6]. Kim *et al.* [7] have argued that "personality is closely tied to preferences for learning materials in that a particular format reflects a person's preferences for taking in information and making decisions." Tlili *et al.* [2] highlighted the importance of considering the learner's personality in computer based learning. In the literature, very few studies have considered the learner's personality in e-learning systems [8]–[10]. In addition, despite the recent attention that educational games are gaining due to their features that can make them very effective in delivering personalized learning

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contents to students, no research work has reported the consideration of learner's personality in educational games to provide a personalized learning-playing process. This might be because designing educational games is more complicated than designing traditional e-learning systems, since they are dynamic, packed with action and learning is an integral part of the game play [2].

Therefore, this paper presents a personalized educational game for teaching Certificate of Informatics and Internet (C2I) subject based on learner's personality, specifically the well-known introvert/extrovert personality dimension [11]. Besides, this paper investigates the impact of this personalized game on learner's motivation, cognitive load and technology acceptance by comparing to a non-personalized version of it. Due to time constraints during the experiment, the experiment focused solely on personality, and some other important factors, such as learning outcomes (i.e., learning achievements), were not investigated.

The rest of the paper is structured as follows: Section 2 presents related work regarding introvert/extrovert personality dimension and personalized learning systems. Section 3 describes the designed personalized game. Section 4 presents the conducted experiment, while the obtained results are listed in section 5. Finally, section 6 discusses these results, concludes the paper and presents future directions based on this research.

II. RELATED WORK

This section presents introvert/extrovert personality dimension. It also presents an overview of personalized learning systems based on learner's personality, as reported in the literature.

A. INTROVERT AND EXTROVERT PERSONALITY DIMENSION

Peoples have different reactions and perceptions toward a given situation or approach, and these differences are caused by variation in personality traits [12]. Various definitions of personality exist in the literature, but there is still no generally accepted definition of it. According to Weinberg and Gould [13], personality describes the characteristics that make a person unique. Allport [14] considered personality as "the dynamic organization within the individual of those psychophysical systems that determine his characteristics, behavior and thought." Mount *et al.* [15] describes personality traits as stable psychological characteristics which define people's behavior and cognitive style. Many studies in the literature showed that personality affects learners in many ways, such as perception of educational method [16], preference of game genre and game design elements in learning environments [17], [18], and learning performance [19]. For instance, Chen *et al.* [20] found that differences of the learners' personalities can impact their learning behaviours in MOOCs.

Various personality models with different personality dimensions have been presented in the literature. One of

these dimensions is introvert/extrovert dimension, which is found in many personality models, such as the Big Five Factor and Myers Briggs. It is well-known and has been considered a hot topic in recent years [11]. The terms "introversion" and "extraversion" go back to the 1920s and are attributed to the psychologist Jung and Baynes [21]. The term introversion is associated with people who draw their energy from inner world of ideas, imagery, and reflection. Extroversion, on the other hand, is associated with action oriented people who draw their energy from the outer world. Zafar and Meenakshi [22] and Walsh [23] stated that introverts are less self-confident and less risk takers than extroverts. Costa and McCrae [24] identified 6 facets that correspond to each trait in the Big Five Factor model, namely extraversion, neuroticism, agreeableness, conscientiousness, and openness to experience. On the other hand, the introversion trait is considered as the opposite trait to extraversion. The six facets that are related to extraversion, as defined by Costa and McCrae [24], are as follows:

- *Warmth*: They are friendly and like others by showing warmth and affection.
- *Excitement seeking*: They get bored easily and seek excitement and action.
- *Activity*: They are energetic, full of life and like movement.
- *Assertiveness*: They are self-confident and usually the leaders of their groups.
- *Gregariousness*: They do not like being alone and prefer the company of others.
- *Positive emotions*: They are full of positive feelings.

Personality is also found to be related with learners' learning style, since introvert learners are thinkers and prefer reflective learning, while extrovert learners prefer active and interactive learning [25]. Research conducted by Johnson *et al.* [26] found that introverts have more blood flow than extroverts in brain areas, which is primarily responsible for remembering, solving problems and planning [27]. Furthermore, learner's personality is found to influence the preferences of using particular game elements. For instance, Jia *et al.* [28] found that extrovert learners have high positive attitudes towards using the leaderboard and progress bar game elements, while introvert learners have not. Codish and Ravid [29] found that extrovert learners prefer using badges more than introvert learners.

Several research studies highlighted that personality can affect cognitive load of individuals [30], [31]. In this context, Eysenck [32] pointed out in his personality model that introvert and extrovert people may have different cognitive load based on the arousal degree within a given learning environment. Additionally, Nuckcheddy [33] showed through a literature review that personality, through the extrovert and introvert characteristics, can affect individuals' motivation level in a work place. It is seen that introvert and extrovert people differently cope with the two motivation factors, namely motivators and hygiene factors, reported in the Frederick Herzberg's theory of motivation [34]. For instance,

introvert people effectively cope with hygiene factors, such as supervision and relationships, while extrovert people effectively cope with the presence of actual motivators, such as achievement and recognition. Similarly, Dinger *et al.* [35] argued that it is easy to motivate introvert learners; however, it is not the case with extrovert learners. Furthermore, several studies revealed that personality traits, as a psychological factor, can affect individuals' technology acceptance, such as smart phones [36]–[39]. For instance, Svendsen *et al.* [38] showed that extrovert personality is positively correlated with behavioural intention to use a particular technology. Therefore, it is assumed that providing personalized learning, according to personality, might enhance learners' motivation, cognitive load and technology acceptance. Personalized learning systems according to personality are further detailed in the next section.

B. PERSONALIZED LEARNING SYSTEMS

Uniform learning approach can make learners perform poorer academically. Therefore, researchers and practitioners have used personalized learning systems which aim to identify learner's characteristics and apply the learning strategies that suit them the most. Personalized learning systems aim to provide personalized learning resources for learners, including the delivered learning content and the learner preferred interfaces for learning [40]. Brusilovsky [41] mentioned two adaptation approaches which can be used in developing web-based personalized learning systems, namely adaptive presentation and adaptive navigation support. Adaptive presentation presents personalized learning content for learners, while adaptive navigation support presents personalized learning paths which can guide learners to explore the learning content. Besides, various studies have further reported the importance of providing personalized user interfaces to match the learner's learning habits [42]. Many researchers have seen that effective learning systems should provide personalized learning content, path and experience for learners [43], [44]. According to the National Academy of Engineering [5], advance personalized learning is one of the 14 most important challenges of the 21st Century.

Various personalized learning systems in the literature have been developed based on different parameters that represent learners' characteristics or preferences [45]. One of these parameters is "personality" which is a widely recognized indicator of individual differences [6]. Despite the importance of taking into consideration learner's personality in computer based learning [2], few personalized learning systems based on learner's personality have actually been developed. For instance, El Bachari *et al.* [9] developed a system which is called LearnFit. This system determines learner's personality using Myers Briggs Type Indicator (MBTI) questionnaire. It then provides a personalized learning strategy based on each personality. In another learning system by Fatahi *et al.* [10], the learners had to answer also the MBTI questionnaire in order to determine their personalities. Then, based on their learning preferences whether they prefer individual learning

or group learning), the system assigns a virtual classmate agent that has an opposite personality to each identified learner's personality. Abrahamian *et al.* [8] developed a learning system which provides a personalized user interface based on each learner's personality after answering the MBTI questionnaire.

When it comes to personalized educational games, several such games have been developed based on several personalization parameters, such as learning style [46], emotion [47], spatial visualization skills [48] and difficulty level [49]. However, to the best of our knowledge, no study has yet reported the development of a personalized educational game based on learners' personalities. Most studies focused mainly on implicitly identifying learners' personalities based on their gaming behaviours (e.g., [17], [50]). Therefore, this study contributes to extend the literature by developing a personalized educational game based on learner's personality, specifically the extraversion/introversion personality dimension. It then investigates the impact of the personalization process on learners' motivation, cognitive load and technology acceptance (discussed above). Specifically, this study explores the following research questions:

1. Do personalized educational games based on personality significantly enhance learning motivation in comparison to non-personalized educational games?
2. Do personalized educational games based on personality significantly reduce learners' cognitive load in comparison to non-personalized educational games?
3. Do the learners who learn with personalized educational games based on personality show significantly higher degree technology acceptance in terms of perceived ease of use, perceived usefulness and perceived intention to use the games than those who learn with non-personalized educational games?

III. GAME IMPLEMENTATION

In this research, an online educational game Eirl for C2I is developed, which aims to teach Certificate of Informatics and Internet (C2I) subject. This subject is taught in universities in various countries, such as in Tunisia and France. The learners take the game character "Eirl" to safety in order to win. While doing that, the learners learn about the role of different computer hardware and software components (e.g., RAM, Microsoft Office, etc.). They also learn about online informational websites and how they can be used (e.g., Forum, Blog, etc.). Eirl for C2I utilizes web platform and therefore can work on both computers and mobile devices. This allows learners to use it on their computers (in case they do not have smartphones) and via their mobile handsets anytime and anywhere, even in rural places where computers cannot be reached. The motivation behind choosing the web platform is to avoid the incompatibility of mobile platforms (i.e., the games that are developed for Android operating systems cannot run on iOS operating systems and vice versa). This can limit the usability of the game by learners. Eirl for C2I detects the type of input (touch screen or mouse/keyboard) generated

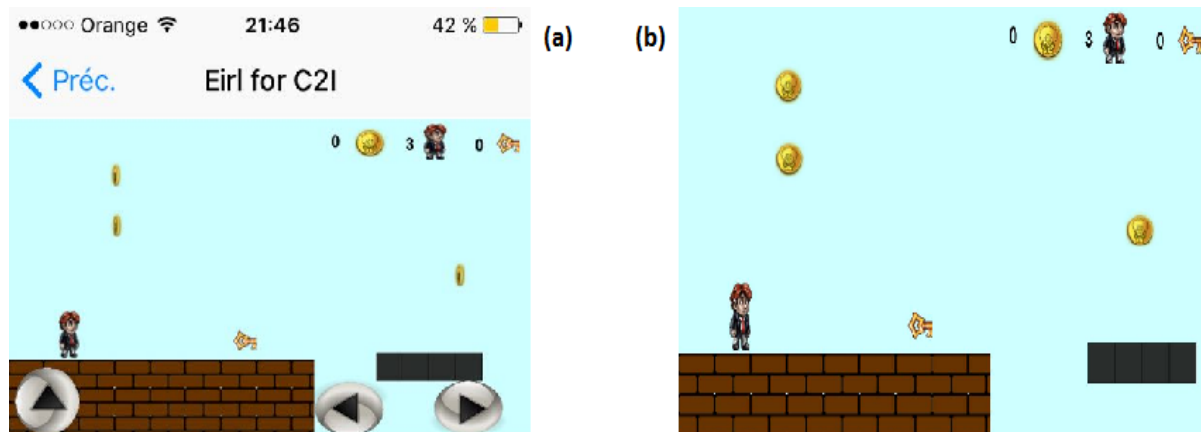


FIGURE 1. The game on both computer and mobile platforms.

by learners and provides the appropriate game controllers needed to play and learn (touch screen buttons in case learners are on their mobile devices, or mouse and keyboard in case they are using computer). As shown in figure 1(a), if the game is running on a mobile device, touch buttons are generated on the screen, which are used to control the game. Otherwise, these buttons are not generated and the learner will be using the ordinary game inputs, namely the keyboard and mouse, to control the game, as shown in figure 1(b). Furthermore, to avoid any connection problems, the game was designed and optimized to work even on low Internet bandwidth.

To provide a personalized game, the game learning environment starts by modelling the learner's personality. In this step, the game character "Eirl" starts introducing himself to learners. He then asks them to answer some questions in order to get to know them as well. These questions are related to the introversion/extroversion dimension defined in the Big Five Inventory (BFI) questionnaire, which has been used widely and is found reliable [51]. The learner modelling process is presented in a storytelling form. It is because individuals try to present themselves in a more acceptable fashion when they feel they are assessed by others [52]. After the modelling process, learners are redirected to the game learning environment where they best fit in based on their personalities. In each game environment, different game elements are implemented and a particular learning strategy is applied, based on the various features of introvert and extrovert learners (identified in "Introvert and extrovert personality dimension" section). These two environments are described in the following sections.

A. GAME LEARNING ENVIRONMENT FOR INTROVERT LEARNERS

Since introvert learners are reflective, the reflective learning strategy is applied. Boud *et al.* [53] defined reflective learning as "those intellectual and affective activities in which individuals engage to explore their experiences in order to

lead to new understandings and appreciations." This can be accomplished using quiz based environment with reflection triggering questions. In this context, the first three stages of the MIRROR Computer Supported Reflective Learning (CSRL) model were implemented [54]. The first stage plan and do work aims to conduct an activity and observe it. In this stage, the game quiz questions are prepared and the learning data, namely the learners' given answers, during the learning-playing process are collected and prepared for the reflection session. By collecting these answers, the learners can later look back and see what was done. Consequently, reflection is triggered by the learners eager to find out how they did on the quiz. The second stage initiate reflection is where the reflection cycle starts. This is triggered using various reflection questions within the quiz to enable learners to think back about their experience. The third stage Conduct reflection session is about how the game conducts the reflection stage. This is achieved by using the collected learners' answers during the stage 1 where the learners can see their final obtained score. Besides, they can see their submitted answers and the correct answers, hence compare the results and re-evaluate their experiences.

Furthermore, since introvert learners are less self-confident, a rewarding system game element is used within this game environment. In this context, a clapping sound effect is played whenever the learners give correct answers. This can make them feel that they did well during learning, hence be more self-confident. Also, for each correct answer the learner gives, additional points are added to his/her game score. In particular, since introvert learners do not prefer leaderboards, this score is locally stored and only the learner can see it.

B. GAME LEARNING ENVIRONMENT FOR EXTROVERT LEARNERS

Since extrovert learners are active, the active learning strategy is applied. Dodge [55] stated that this strategy "puts the

responsibility of organizing what is to be learned in the hands of the learners themselves.” De Weck *et al.* [56] defined active learning as a less passive method to engage learners directly in problem solving activities. This learning strategy is achieved by providing a game environment where learners can freely explore it and discover the different game learning activities. For instance, instead of simply answering quizzes (as given in the introvert game learning environment), the learners have to collect several coins where each coin will give them information regarding a particular topic in C2I. Additionally, based on each decision made or step progression, an immediate feedback is presented to further guide learners while learning-playing. This feedback can be a displayed text or a game result (e.g., if the learner gives a wrong answer, he/she loses a game life). In addition, every time the learners fail to finish a particular game activity, they can repeat it until they master it. This game environment makes learners active, where they are learning while solving different game activities.

Furthermore, since extrovert learners are sociable and prefer taking risks, two game elements are respectively implemented, namely Non Player Characters (NPCs) and enemies. The first game element aims to further stimulate the sociable side of extrovert learners, by allowing them to talk to NPCs in order to guide them when needed. The second game element aims to add the challenge criterion while learning, since learners have to defeat different enemies in order to solve a particular game activity. This can make them more motivated to learn.

IV. METHOD

A. PARTICIPANTS

Fifty one undergraduate learners, aged between 18 and 20, voluntarily participated in this experiment. These learners are all enrolled in a C2I course within a public university in Tunisia. Additionally, they are all majoring in computer science, hence they have good skills towards using computers. Furthermore, these learners reported that they have played computer games before. Table 1 presents the statistical distribution of learners. Specifically, the learners’ personalities were identified using the Big Five Inventory (BFI) questionnaire which is a popular instrument in the field of psychology. It contains 44 statements about five personality dimensions in Five Factor Model (FFM).

TABLE 1. Statistical distribution of learners.

Personality	Male	Female	Total
<i>Introvert</i>	9	11	21
<i>Extrovert</i>	12	18	30

B. EXPERIMENTAL PROCEDURE

A quasi-experiment was designed by randomly assigning learners to two different groups, namely experimental and control. The experimental group had twenty six learners

and used the personalized educational game to learn C2I (13 learners are introvert and 13 learners are extrovert). The control group had twenty five learners and used the non-personalized game to learn C2I. Before the start of the learning-playing process using the designed educational game, the instructor took 10 minutes to explain to the learners the main objective of this experiment. He then gave them some instructions on how to play the game. Besides, the learners in both groups (experimental and control) answered a motivation, questionnaire before playing the educational game. After that, learners in the experimental group learned with the personalized educational game; on the other hand, the control group learned with a non personalized educational game. Both versions of the game contain the same learning content and background and they were designed by the same instructor to ensure the consistency of the implemented learning content. Finally, the learners in both groups took again the same motivation questionnaire, in addition to cognitive load and technology acceptance questionnaires.

C. RESEARCH INSTRUMENTS

Three instruments were used by both groups (control and experimental) to evaluate the impact of the personalized educational game on the learning process, as described below:

Motivation questionnaire: It is a seven point Likert scale questionnaire which was modified from Pintrich and De Groot [57]. The learners started by taking a pre-motivation questionnaire which evaluated their motivation level before the start of the learning-playing activity. After the learning-playing activity, the learners also took a post-motivation questionnaire (as the pre-motivation questionnaire). This questionnaire helped to evaluate the impact of the personalized and non-personalized educational game on the learner’s learning motivation. The Cronbach’s alpha was calculated to measure the internal consistency and it was equal to 0.83. This means that the questionnaire is reliable since Cronbach’s alpha value is greater than 0.7 (Yu, 2001).

Cognitive load questionnaire: It is a seven point Likert scale questionnaire and it was taken after the learning-playing activity. This questionnaire calculates the two dimensions namely mental load and mental effort. Mental load refers to the interaction between task and subject characteristics [58]. Mental effort, on the other hand, reflects the aspect of cognitive load related to the way of presenting the learning content or the adopted strategy for guiding the learners to learn [59]. Each dimension has three statements. This questionnaire helped to evaluate the impact of the designed games on the learner’s cognitive load. The Cronbach’s alpha was calculated to measure the internal consistency for the cognitive load questionnaire. It was equal to 0.75 and 0.79 for the mental load and mental effort dimensions respectively. Consequently, the questionnaire is considered reliable since all the Cronbach’s alpha values are greater than 0.7 [60].

Technology acceptance questionnaire: It is a seven point Likert scale questionnaire with ten statements and it was taken after the learning-playing activity. This questionnaire is

TABLE 2. T-test results of the pre- motivation questionnaire ratings of the two groups.

			Paired Differences		t	Sig. (2-tailed)	
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference			
				Lower			Upper
<i>Pair 1:</i> <i>Control group</i>	0.43	1.64	0.32	0.39	1.40	2.18	0.03*
<i>Pair 2 :</i> <i>Experimental group</i>	0.46	1.35	0.26	-0.92	1.00	1.71	0.02*

*p < .05.

adapted from Chu et al. (2010a, b) and it calculates the three dimensions defined in the Technology Acceptance Model (TAM), namely Ease of Use, Usefulness and Behavioral Intention to Use the game [61]. The Ease Of Use (EOU) defines the degree to which learners find the game easy to use and free of effort. The Usefulness (U) defines the degree to which learners think that the game will enhance their level of knowledge while learning. The Behavioral Intention to Use the game (BIU) defines the degree to which learners are willing to use the game again in the future to learn C2I. The Cronbach’s alpha values for the three dimensions of the technology acceptance questionnaire, namely ease of use, usefulness and behavioral intention to use the game were equal to 0.81, 0.85 and 0.91 respectively. This means that the questionnaire is reliable since all the Cronbach’s alpha values are greater than 0.7 [60].

V. RESULTS

This section presents the obtained results of the personalization process after analyzing the learners’ data collected using the above presented instruments.

A. IMPACT OF LEARNER’S MOTIVATION

The motivation questionnaire results of both the control and experimental groups were then analyzed using the paired t-test method. This method is appropriate in this context because the same group of learners answered both motivation questionnaires (pre and post). This can help to separately investigate the impact of the personalized and non-personalized games on the motivation for the experimental and control groups respectively. Table 2 presents the results of the paired t-test method.

As shown in table 2, both personalized and non-personalized versions of the game have significantly enhanced the motivation level of both the control group, where p is equal to 0.03 and less than 0.05, and the experimental group, where p is equal to 0.02 and less than 0.05. Furthermore, to investigate if the learners who learnt with the personalized educational game based on personality show significantly higher learning motivation than those who learnt with the non-personalized educational game, the pre and post motivation questionnaire results of both the control and

experimental groups were analyzed and compared. In particular, the pre-motivation questionnaire results were analyzed using the t-test method.

As shown in table 3, the mean and standard deviation values are respectively 4.85 and 1.32 for the control group, while, they are 5.24 and 1.48 for the experimental group. The t-test results showed no significant difference between the pre-motivation questionnaire results of the two groups, since t is equal to -1.48 and p is greater than .05. Therefore, the both groups (control and experimental) had the same motivation level before participating in the learning-playing activity.

TABLE 3. T-test results of the pre- motivation questionnaire ratings of the two groups.

Group	N	Mean	S.D	t
<i>Control</i>	25	4.85	1.32	
<i>Experimental</i>	26	5.24	1.48	-1.48

After the learning-playing activity, the analysis of covariance ANCOVA was used to test the difference between the two groups by using the pre-motivation questionnaire as the covariate and the post-motivation questionnaire as dependent variable. As shown in table 4, the mean and standard deviation of the post-motivation questionnaires were respectively 5.28 and 1.01 for the control group. However, the mean and standard deviation were 5.70 and 0.95 for the experimental group. Thus, the post-motivation questionnaire ratings of the two groups were not significantly different, since F is equal to 1.82 and p is greater than .05. To conclude, both the personalized and non-personalized games have significantly enhanced

TABLE 4. ANCOVA results of the post- motivation questionnaire ratings of the two groups.

Group	N	Mean	S.D	Mean Square	F	Sig
<i>Control</i>	25	5.28	1.01	3.46	1.82	0.18
<i>Experimental</i>	26	5.70	0.95			

TABLE 5. T-test results of the cognitive load questionnaire ratings of the two groups.

Cognitive Load	Group	N	Mean	S.D	T
<i>Mental Load</i>	Control	25	3.55	1.65	2.05*
	Experimental	26	2.74	1.11	
<i>Mental Effort</i>	Control	25	4.14	1.53	3.64*
	Experimental	26	2.64	1.40	

the motivation of the experimental and control group respectively. However, there was no significant difference on the improvement of motivation between the experimental group and the control group. This implies that both the personalized educational game and the non-personalized version of the game can enhance motivation equally well.

B. IMPACT OF LEARNER'S COGNITIVE LOAD

The cognitive load questionnaire was then analyzed using the t-test method. As shown in table 5, the t-test results highlight a significant difference between the cognitive load of the control and the experimental group in both dimensions, namely mental load and mental effort. Thus, the personalized educational game helped in decreasing the cognitive load required by learners to learn C2I from 3.55 to 2.74 for the mental load dimension and from 4.14 to 2.64 for the mental effort dimension. This shows that personalizing the game elements and the way of presenting the learning content in the game environment based on personality can significantly reduce the learning cognitive load compared to learning with a non-personalized game.

C. IMPACT OF LEARNER'S TECHNOLOGY ACCEPTANCE

The learners' feedback regarding the usefulness, ease of use and intention to use the non-personalized and a personalized version of the game were then analyzed using the t-test method. As shown in table 6, the t-test results highlight a significant difference only in the usefulness and intention to use the game dimensions. In particular, it is found that learners who used the personalized educational game reported higher positive feedback regarding the perceived usefulness and their behavioural intention to use this game in the future. However, no significant difference was found regarding the ease of use dimension.

VI. DISCUSSION AND CONCLUSION

While none of the previous studies in the literature considered learner's personality in digital educational games [2], this paper presented a personalized educational game, based on learner's personality, to teach the C2I subject. It also investigated the impact of this game on learners' motivation, cognitive load and technology acceptance, compared to a non-personalized version of the game.

The experimental results showed that the personalized educational game has no significant difference in comparison with its non-personalized version regarding learner's motivation. The reason may be that the educational games by their virtue improve learners' motivation, whether they are personalized or not. Many previous studies have reported similar results that educational games, due to their fun, engagement and challenging feature, are able to promote the learners' learning motivations [62]–[65]. However, further investigations are needed to explore whether incorporation of various design theories (e.g., Keller's ARCS Model of Motivational Design Theories) could improve the design of the personalized educational game to promote motivation for learners even further.

In addition, the findings highlighted that the personalization process provided within the educational game reduced learner's cognitive load while learning. In particular, providing a specific learning style which matches each learner's personality in each game environment, specifically active learning for extrovert learners and reflective learning for introvert learners, helped reduce mental effort and mental load imposed on working memory to process the given learning content within the game. Previous research studies have highlighted a relation between the learner's learning style and cognitive load [66], [67]. Additionally, the personalized educational game provided personalized arousal elements in the game environment by, for instance, providing more arousal elements for extrovert learners, like NPCs to communicate with and enemies to challenge, and less arousal elements for the introvert learners. This helped to reduce their cognitive load in comparison with the control group [32].

Moreover, the findings reveal that the learners who used the personalized educational game to learn C2I reported the usefulness of the game more compared to those who learned with the non-personalized game. This means that those learners who learned using a personalized educational game based on personality felt the benefits of personalization of learning in enhancing their learning achievements. These results are consistent with the findings of Hwang *et al.* [46], who used a personalized educational game based on learning styles. In their study also, the learners who used the personalized game found it more useful than the learners who used the non-personalized version of the game. In comparison with the ratings given by the control group, it should be noted that the learners in the experimental group gave significantly higher ratings for "perceived usefulness".

This can be explained with the personalized version of the game enabled learners of the experimental group to learn in a way that matched their information perceiving and processing, hence they perceived more usefulness to use the game than those of the control group. Consequently, the learners of the experimental group gave also significantly higher ratings for "perceived intention to use the game" compared to the learners of the control group. This means that the learners who used the personalized educational game were more willing to use it again in the future, compared to the learners

TABLE 6. T-test results of the technology acceptance questionnaire ratings of the two groups.

TAM	Group	N.	Mean	S.D	T
<i>Ease of Use (EOU)</i>	Control	25	4.40	1.18	-0.251
	Experimental	26	4.48	0.99	
<i>Usefulness (U)</i>	Control	25	4.80	1.48	-2.13*
	Experimental	26	5.58	1.11	
<i>Behavioral Intention to Use (BIU)</i>	Control	25	4.08	1.72	-2.25*
	Experimental	26	5.12	1.56	

*p < .05.

who used the non-personalized game. Recent studies have also reported that perceived usefulness is a strong predictor of behavioral intention to use a particular system [68], [69]. Furthermore, no difference was found between the control and experimental groups regarding the perceived ease of use of both educational games (personalized and non-personalized). This may be due to the fact that both personalized and non-personalized educational games were designed in such a way that they required very little effort, since they could be played using just simple clicks (with keyboard or touch screen). Therefore, the learners in both groups found these games easy to use regardless of the availability of personalization. Consequently, no significant difference was noticed regarding the perceived ease of use.

The findings of this study can be used by educators to provide personalized game learning environments based on learner's personality, specifically for introvert/extrovert learners. Besides, this study can push researchers to further investigate the importance of learner's personality in educational games, since the work presented in this study is an initial step in this direction. Despite the importance of the findings, some limitations need to be noted for this research which may limit the generalizability of the results. For instance, this study did not investigate the impact of the personalization process on the learning outcomes. Besides, the sample size of this study was limited. Future directions could focus on investigating the effect of the other personality dimensions presented in the Five Factor Model (FFM) in an educational game context, as they were proved to affect learning as well. Furthermore, additional factors that may affect learners' experience with educational games, such as prior knowledge and online learning behaviors, should be considered while personalizing the environment.

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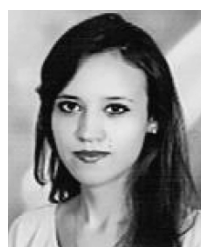
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