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Role of personality in computer based learning

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A R T I C L E I N F O

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A B S T R A C T

With the rapid growth of technology enhanced learning, new mediums for learning have emerged. One of these mediums is computer based learning where the main concern is how to design a computer based learning system which takes into consideration the learners' differences. Personality is considered as one of the most critical sources of individual differences. This study investigates how personality differences within learners can affect computer based learning, through a comprehensive review of the literature. The highlighted results from the obtained nineteen studies are: (a) the most referred to personality model in computer based learning is MBTI; (b) personality traits affect how learners prefer learning content and learning approach like collecting information, communicating with instructor and peer, study behavior, acting and performing; (c) a new model of personality variables should be considered in computer based learning by taking all interested researchers and practitioners into accounts; and (d) the traditional questionnaire approach which is still the pre-dominant method to identify the learner's personality; and this needs to be changed with new potential of big data and learning analytics. Furthermore, this study presents a new implicit approach using learning analytics instead of questionnaire-based approach to identify the learner's personality.

1. Introduction

Technological advancements, especially Information and Communications Technologies (ICT), in recent years have made computers vital in education by offering new learning mediums, contents and strategies served through computers. Consequently, computer based technologies are gaining an increasing attention in higher education. For example, the public educational institutions of United States reduced the ratios of K-12 students per computer from 6.6 in 2000 to 3.1 in 2008 (Snyder & Dillow, 2011). Besides, according to the U.S. Department of Education, 97% of school classrooms in 2009 had at least one computer, while 93% also had Internet access (National Center for Education Statistics, 2010). In this context, Computer Based Learning (CBL) can be listed as an example of using technology in education. It is considered as the use of any form of learning software (installed or online programs/applications) with personal computers without the interventions of instructors (Bouck, Meyer, Satsangi, Savage, & Hunley, 2015; Lee, 2006). Bahreman, Chang, Amistad, and Garn (2016) stated that the role of computers in CBL is more like meta-tutors where they trace and record the learner's progress. Besides, they give timely and explicit feedback. Algahtani (2011) mentioned that CBL can be used in either of the two ways: computer managed instruction where the main purpose of computers is to store and retrieve information which helps in the management of education. Another form of CBL is computer assisted learning where computers are used instead of the traditional methods for learning within or outside the class through interactive software tools. Magen-Nagar and Peled (2013) stated that computerized learning tools can create many changes in teaching, learning and thinking processes.

Learners have different individual characteristics and because of that, they behave differently in CBL (Essalmi, Ayed, Jemni, Kinshuk, & Graf, 2010, 2015; Graf, Liu, Chen, & Yang, 2009). One of the characteristics is "personality", which is widely identified as an important indicator of individual differences (Irani, Telg, Scherler, & Harrington, 2003). While there is no agreed upon definition of personality in the literature, two of the classic definitions of

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personality belongs to Allport (1961) and Child (1968). Allport (1961) considered personality as a unique psychological system located inside individuals. Child (1968) on the other hand considered personality as an internal factor that gives consistency over time for the individual's behavior. According to Zafar and Meenakshi (2012), personality is an integrated part of individuals. It comes with them to a particular situation and leaves with them when they go. Quercia, Kosinski, Stillwell, and Crowcroft (2011) stated that the individuals' real world actions, taste and behaviors have been found significantly connected to their personalities. Based on their personalities, individuals make daily personal or professional judgments and decisions such as whom to be friend, marry, trust, hire, or elect as president (Youyou, Kosinski, & Stillwell, 2015). Studies have also highlighted that learners have different responses to the educational methods, based on their personality (Irani et al., 2003). Besides, personality has been found to be associated with technology related to human computer interaction (Svendsen, Johnsen, Almås-Sørensen, & Vittersø, 2013). Therefore, this paper investigates how personality differences can affect computer based learning. A model of the variables is then proposed to provide an adaptive CBL based on personality.

The rest of the paper is structured as follows: Section 2 presents a literature review regarding CBL and personality models. Section 3 presents the research method used in this research to investigate the effect of personality in CBL. Section 4 describes the results of the investigation, followed by the discussion of the results in Section 5. Section 6 concludes the paper with a summary of the findings, the limitations of the current study and potential research directions.

2. Literature review

This section explores various definitions of computer based learning, and their strengths and weaknesses. Various personality models, available in the literature, are then discussed based on different personality theories. This review is aimed to understand the difference between the different personality models in terms of their unique effects on computer based learning.

2.1. Computer based learning

Computers can potentially be used to overcome the insufficiency of traditional learning for educating individuals or helping them gain the required learning skills (Tareef, 2014). CBL is the use of computers for learning activities where an educational software is run on computers to deliver a particular part or the whole learning subject (Serin, 2011). This software is historically classified into five categories, namely drill and practice, tutorial, simulation, hypermedia and educational games (Alessi & Trollip, 2001). In CBL, the learning content is provided for learners in different forms such as drawings, graphics, animation, music and plenty materials (Serin, 2011). It is considered a lot richer than the content provided in traditional learning in classrooms. Besides, the teaching methods become more effective than those offered in traditional learning. For instance, the learners can get interactive, motivating or immersive teaching methods through computer technology by using computer games which are not satisfied in traditional classrooms. CBL helps the development of decision-making, problem solving, data-processing and communication capabilities skills within learners (Bakac, Tasoglu, & Akbay, 2011). As a result, learners become motivated, active and had positive attitudes (Liao, 2007; Senteni, 2004).

According to the Internet World Stats (Internet World Stats, 2015), the average growth rate of Internet users in the world between 2000 and 2015 is 832.5%. This created significant opportunities for CBL to evolve and establish its presence online, resulting in wide adoption by universities and other educational organizations. Various terms, such as web-based learning, online learning, and distance learning, have been used interchangeably to represent the concept of CBL, with subtle, yet consequential differences (Tsai & Machado, 2002). E-learning is the latest term added to this list and has replaced all the previous terms. It includes the use of activities involving computers and interactive networks simultaneously (Punnoose, 2012). An e-learning environment provides flexible learning process for learners where they can learn without being limited to particular time and location. This allows for self-paced learning, and offers an alternative learning experience that is different than the traditional one (Carver, Howard, & Lane, 1999; Graff, 2003; Terrell & Dringus, 2000). Nowadays, many colleges and universities are changing the learning mode from traditional classrooms to e-learning (Huang, Lin, & Huang, 2012).

While the adoption of CBL is on the rise, researchers and practitioners have also identified several weaknesses. According to Iowa State University (2011), technical difficulties such as slow Internet connection or older computers can affect the learning process negatively and make it frustrating. Arkorful and Abaidoo (2014) stated that CBL and e-learning requires money and time to put a working architecture such as use of websites. Moreover, they stated that in CBL, it is easy to fake answers through copy paste and plagiarism. Also, learners with low level of motivation may not cope with CBL and fall behind. Furthermore, Instructor may not always be available when learners are looking for help. Dina and Ciornei (2013) mentioned that CBL through its excessive learning individualization can affect negatively the educational process by isolating learners which can lead to the loss of emotional connection with teachers.

Literature indicates many different personality models that can be used to classify individual learners' personalities. Some of these models are investigated in the next section.

2.2. Personality models

A number of personality models have been proposed in the literature to understand the individuals' behaviors and characteristics. Each one of these models is based on a different personality theory and presents different personality traits. Bayne (2004) claimed that the differences of the learners' personalities result in different ways of learners' involvement in the learning progress regardless of their personal interests or the degree of cognitive development. This section gives an overview of some of the commonly used personality models.

2.2.1. Myers Briggs personality types indicator

Carl Jung's theory of Psychological Types considered that individuals are either introverts or extraverts. Introverts are people who move their energy toward their inner world of feelings and ideas. Extraverts are people who move their energy toward the external world of individuals and activities (Jung, 1971). Jung (1971) argued that the way of processing information differs from person to person, depending on their personalities. In particular, individuals gather information either by sensing or by intuition. Then, they can decide and make judgment based on this information either by feeling or by thinking about them (Myers & McCaulley, 1985). The Myers Briggs Type Indicator is derived from the Carl Jung's theory (Myers, McCaulley, Quenk, & Hammer, 1998). It divides personality types and preferences into four dichotomies, as follows:

(1) *Extraversion (E) or Introversion (I)* is from where a person gets his/her energy.

(2) *Sensing (S) or Intuition (N)* is how a person prefers to gather information.
(3) *Thinking (T) or Feeling (F)* is how a person prefers to make decisions.
(4) *Judging (J) or Perceiving (P)* is how a person handles the external world.

The combinations of the above dichotomies result in a total of 16 personality types and are typically denoted by four letters to represent a person's tendencies on the four dichotomies (O'brien, Bernold, & duane, 1998). For example, ENTJ stands for Extroversion, Intuition, Thinking, and Judging. The Myers Briggs Type Indicator has been widely used and validated extensively in the education domain (Myers et al., 1998).

2.2.2. Big five factors

The five-factor model of personality is a hierarchical organization of personality traits in terms of five basic dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism (McCrae & John, 1992). It is referred to as OCEAN, being the acronym of the five presented dimensions. These dimensions are not based on a particular theoretical perspective but are derived from the analyses of the natural language words used by individuals to describe themselves or others (John & Srivastava, 1999). The five dimensions are described as follows:

(1) *Openness to experience* is the degree of a person's intellectual curiosity, creativity, and preference for new experiences.
(2) *Conscientiousness* is the degree of a person's tendency toward self-discipline, competence, and achievement persistence.
(3) *Extraversion* is the degree of being sociable and outgoing.
(4) *Agreeableness* is the degree of being cooperative and willing to help others.
(5) *Neuroticism* is the degree of being emotionally stable and self-control.

2.2.3. Hans Eysenck's model

Eysenck considered that the difference within individuals' personalities is coming from the inherited genetics. Thus, his main focus was on temperament (Boeree, 2006). Besides, he considered personality as a reflection of the brain behavior where the differences in the cortical arousal is the source of the different personality types (Kar, 2013). Eysenck divided personality into three dimensions, namely Psychoticism, Extraversion and Neuroticism. They are referred to as the PEN model and are detailed as follows (Ashton, 2013; Carducci, 2009; Eysenck, 1990):

(1) *Extraversion dimension* means the same as Jung defined it where extraversion is related to social interest and positive affect.
(2) *Neuroticism dimension* refers to the emotional stability (self-esteem, happiness, etc.).
(3) *Psychoticism dimension* is more recent addition and has not been deeply investigated yet like the two other dimensions. It is more related to character than temperament such as aggressiveness, manipulation and irresponsibility.

To understand the learners' behaviors and how their personalities can affect computer based learning, researchers in their studies referred to one of the above presented personality models to identify the learner's personality in the first place. These studies are investigated in this paper. In particular, the method followed in this research to identify these studies is presented in the next section.

3. Method

This study investigates how personality differences within learners can affect computer based learning. To do so, a comprehensive literature review was conducted using various keywords such as “personality and learning”, “personality in e-learning”, “personality in computer based learning” in different electronic databases. Then, the obtained studies were filtered based on the inclusion/exclusion criteria presented in Table 1.

Based on a comprehensive literature review, to investigate how learner's personality can affect the learning process of individual learners in CBL, this study aims to answer the following research questions:

(1) *What is the most referred to personality model in computer based learning?*
(2) *What variables should be considered by researchers and practitioners to provide an adaptive computer based learning based on personality?*
(3) *How personality differences can affect computer based learning?*

The research question first identify which personality models have been used in the literature to understand the effects of learners' personality in computer based learning. Based on those models, various variables are identified that are important for customizing computer based learning to suit learners' personalities. Finally, this research examines the effects of personality differences.

4. Results

The inclusion/exclusion criteria were applied on different data sources, including ERIC, ScienceDirect, Microsoft Academic Search, IEEE Xplore Digital Library, ACM Digital Library, and JSTOR. The obtained results highlighted 19 studies which were published between 2001 and 2014 in different international conferences and journals. Table 2 presents the data source of each listed study.

The first question explored in this study is as follows:

Research question 1: What is the most referred to personality model in computer based learning?

To answer this question, Table 2 summarizes the referred model to identify personality in each study presented during the literature review.

Based on Table 2 and as shown in Fig. 1, the most referred to personality model in computer based learning is MBTI where 14 studies (among 19) used it to model the learner's personality followed by the Big five factor (4 studies) and Eysenck's model (1 study). This can help researchers to identify which model among other personality models they should choose to identify the learner's personality in CBL.

Once the personality models that have been used in the literature to understand the effects of learners' personality in computer based learning have been identified, the next research question explored in this research is as follows:

Research question 2: What variables should be considered by researchers and practitioners to provide an adaptive computer based learning based on personality?

To identify the important variables, each study in the literature is examined to observe which variables have been investigated by

Table 1
Inclusion and Exclusion criteria.

Inclusion criteria	Exclusion criteria
Must involve computer based learning as a primary condition Must discuss learning using computers or mobile devices. Must be available online.	Studies which do not involve experimental results. Studies which are based on theoretical approaches only.

Table 2
Summary of the presented studies.

Studies	Personality model	Data source
Randler et al. (2014)	Big five factors	ERIC
Arockiam and Selvaraj (2013)	Eysenck personality model	Microsoft Academic Search
Al-Dujaily et al. (2013)	MBTI	ERIC
Bolliger and Erichsen (2013)	MBTI	ERIC
Kim et al. (2013)	MBTI	ScienceDirect
Haron and Sahar (2010)	Big five factors	Microsoft Academic Search
Harrington and Loffredo (2010)	MBTI	Microsoft Academic Search
Danesh and Mortazavi (2010)	Big five factors	IEEE Xplore Digital Library
Fatahi et al. (2009)	MBTI	Microsoft Academic Search
Da Cunha and Greathead (2007)	MBTI	ACM Digital Library
Bishop-Clark et al. (2007)	MBTI	ERIC
Lee and Lee (2006)	MBTI	ERIC
Barkhi and Brozovsky (2003)	MBTI	Microsoft Academic Search
Nakayama et al. (2014)	Big five factors	ERIC
Abrahamian et al. (2004)	MBTI	Microsoft Academic Search
Ellis (2003)	MBTI	Microsoft Academic Search
Irani et al. (2003)	MBTI	Microsoft Academic Search
Daughenbaugh et al. (2002)	KTS/MBTI	ERIC
Moller and Soles (2001)	MBTI	ERIC

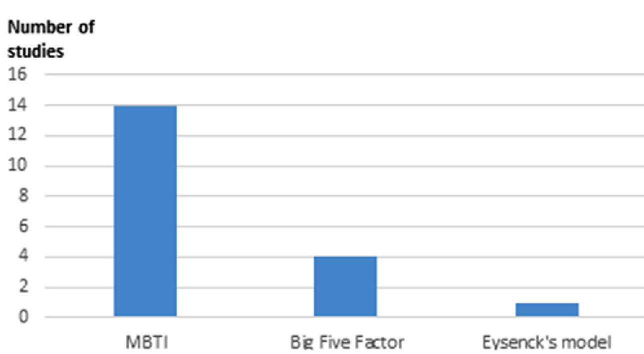

Fig. 1. Personality models in computer based learning.

the researchers in CBL to customize it based on personality. Table 3 presents each observation and the extracted CBL variables.

As shown in Table 3, many personality variables are found in the literature which researchers and practitioners should consider for providing an adaptive computer based learning. Based on the synthesis of those variables, Fig. 2 presents a model of personality variables to consider in computer based learning which can be referred by all interested researchers and practitioners in their context.

As shown in Fig. 2, the learner's personality can affect the feeling or the behavior of a learner while learning. Therefore, further supportive functionalities for learners should be available based on their personalities. For example, a functionality could be provided for introvert learners to decrease their anxiety level while learning with a computer based learning system. Personality can also affect the way a learner adopts a particular computer based learning system. Since computer based learning systems are complex, many elements should be considered based on personality while designing such systems. For example, the instructor or a designer could consider the learner's personality while preparing the learning content and strategies within the system. Furthermore, they could consider how the systems' user interfaces are designed (e.g. fonts and color) and the communication modes provided to the learners (synchronous and asynchronous).

To be able to provide such customization of computer based learning, this research next looks at the effects of personality on computer based learning. The next research question explored in this research is, therefore, as follows:

Research question 3: How personality differences can affect computer based learning?

To answer this research question, this section presents how personality differences affect each identified CBL variable (in research question 2) in each study (in Table 3). The results are discussed below.

Arockiam and Selvaraj (2013) found that learners can recollect information easily with a particular type of design parameters based on their personalities. For example, extrovert learners can easily recollect information presented in blue color with "Times" font style, while, neuroticism learners can easily recollect information presented in green color with "Times" font style. Hence, personality can affect the learners' preferred design parameters of a CBL system interface. In particular, some learners would find a designed interface with a particular color and font more efficient and easier to recollect information from it than others.

Abrahamian, Weinberg, Grady, and Stanton (2004) found that personalized user interfaces based on personality have a significant effect on learning. Besides, they showed that learners preferred more personalized user interfaces. Hence, personality can affect the learner's preferred design parameters for CBL system's interface. In particular, designed interfaces based on personality can affect the learning positively.

Haron and Sahar (2010) and Harrington and Loffredo (2010)

Table 3
The extracted computer based learning variables.

Observation	Investigated variables
Randler et al. (2014) investigated the parameters moderating the willingness and anxiety towards distance learning. One of these parameters is the learners' personalities.	Learner's willingness and anxiety
Arockiam and Selvaraj (2013) investigated the relation between personality and the user interface design parameters, namely color and font style.	User Interface Design parameters (color and font style)
Al-Dujaily et al. (2013) assessed the relation between personality and performance in adaptive and non-adaptive learning systems.	Learner's performance
Bolliger and Erichsen (2013) investigated how the learner's personality can affect the preferred communication modes (synchronous and asynchronous) and the followed learning style (alone or in groups) in online and blended learning environments	communication modes (synchronous/asynchronous), learning style (alone/in groups)
Kim et al. (2013) investigated the impact of the personality trait on the instructional design (depth-first and breadth-first).	instructional design
Haron and Sahar (2010) investigated the factors contributing the adoption of e-learning	Learner's adoption level
Harrington and Loffredo (2010) investigated the factors contributing the adoption of e-learning	Learner's adoption level
Danesh and Mortazavi (2010) investigated whether personality can affect the adoption of distance education.	Learner's adoption level
Fatahi et al. (2009) proposed a new learning system which takes the learner's emotions and personality into consideration. Based on their learning preferences, a Virtual Classmate Agent (VCA) is assigned to them having an opposite personality to the one they have.	learning strategy (opposite personality strategy)
Da Cunha and Greathead (2007) investigated the relation between personality and the performance in code debugging skills in software development	Performance in code debugging
Bishop-Clark et al. (2007) investigated the impact of personality on the learners' performance and satisfaction in an asynchronous web based distance learning course.	learners' performance and satisfaction
Lee and Lee (2006) investigated the impact of personality on the learners learning strategies when they are divided into three groups, namely introverts, extroverts and mixed (introverts and extroverts) in network learning environments.	Learners' learning strategies (mixed and not mixed groups)
Barkhi and Brozovsky (2003) investigated if the learner's personality can influence the communication modes while learning. This was done by investigating the satisfaction and performance of learners in two learning environments, namely face to face and distance learning.	communication modes
Nakayama et al. (2014) investigated how the learner's characteristics, including personality, can affect learning within an online course environment the learner's note taking behavior.	Note taking behavior
Abrahamian et al. (2004) investigated the influence of a personalized computer learning interface on the learners' learning performance.	User Interface Design
Ellis (2003) investigated the relationship between personality type and the learner's behavior within a networked learning environment using asynchronous threaded discussion	behavior of learners
Irani et al. (2003) investigated the relationship between the learners' course perceptions and performance in a distance education course.	learners' performance
Daughenbaugh et al. (2002) investigated the impact of the learners' personalities on their satisfaction in online and traditional introductory computer science courses.	learners' satisfaction
Moller and Soles (2001) investigated the impact of the learners' differences, such as personality, on the way learners learn (learning style) and the preferred learning mediums (learning resources and delivery methods).	Learning styles and mediums

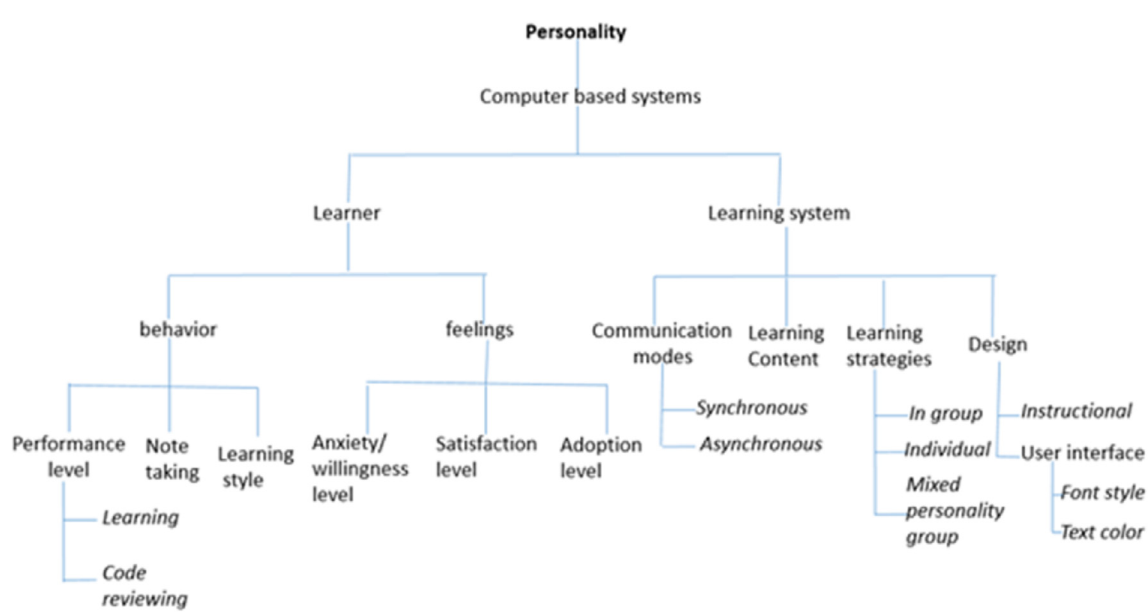

Fig. 2. Model of personality variables in computer based learning.

have highlighted the importance of personality as a parameter for the adoption of e-learning. In particular, Haron and Sahar (2010) showed that conscientiousness and openness personalities have the highest adoption value of e-learning process. Agreeableness personality, on the other hand, has the lowest adoption value. Harrington and Loffredo (2010) found that most introvert people preferred e-learning where they can be alone and far from the others, while, extrovert people preferred face to face learning where they can work in groups. These studies have highlighted that the type of personality can affect the degree of adoption of CBL. Consequently, some learners with particular personalities (e.g. introvert learners) will be interested to participate in CBL experience while others will not (e.g. extrovert learners).

Fatahi, Kazemifard, and Ghasem-Aghaee (2009) found that the learners were satisfied with the learning environment where they learnt with someone having the opposite of their personalities. Hence, personality can affect the learner's choice of his/her learning partner in CBL. In particular, learners seem to prefer a partner with an opposite personality.

Da Cunha and Greathead (2007) found that Intuition-Thinking-(NT) learners are better in code review than non NT learners. This study highlighted that personality can affect the performance in doing certain CBL activities, such as reviewing programming codes.

Randler, Horzum, and Vollmer (2014) highlighted that personality is one of the parameters which moderated the learner's willingness and anxiety towards distance learning. In particular, extrovert learners reported lower Distance Learning Anxiety (DLA) since they are sociable, ambitious and active. However, open-minded learners reported a higher Distance Learning Willingness (DLW). Therefore, personality can affect the degree of learner's willingness and anxiety towards CBL.

Danesh and Mortazavi (2010) investigated the relation between personality and distance education. The obtained results showed that it is hard for extrovert learners to be by themselves in front of the computer without any classmates; thus, they have low performance in distance education mode. Agreeable learners, on the other hand, are successful and have high performance results with any learning method such as traditional learning, e-learning and distance learning. Conscientiousness learners have the highest performance (among the 5 personality traits) and they seek more knowledge and do not cheat while solving the assignments. Low emotional stability learners cannot cope with distance education due to the absence of emotional relationship with the instructor. As a result, personality can affect the adoption of CBL. In particular, it can affect the performance and motivation of learners in CBL.

Al-Dujaily, Kim, and Ryu (2013) assessed the relation between personality and performance in computer based learning systems. The obtained results showed that there is no difference between introvert and extrovert learners in a non-adaptive learning system. However, extrovert learners performed better than introvert learners in adaptive learning systems in terms of the number of correct answers and the time needed for that. Thus, the learner's personality can affect learning process of individual learners in CBL.

Nakayama, Mutsuura, and Yamamoto (2014) investigated how the learner's characteristics, including personality, can affect learning within an online course environment. The obtained results showed that the learner's personality affects how each learner takes notes while learning online. Therefore, the learner's personality can affect the note-taking behavior in CBL.

Lee and Lee (2006) found that the mixed group of learners posted more messages than the introverted group. Besides, they showed that extroverted group is more social and interactive than the introverted group. Furthermore, the extroverted group showed less metacognitive interaction than the mixed group. Ellis (2003) proposed seven recommendations for online learning which consider the personality traits differences. These recommendations are as follows: (1) Online environments need to be well-structured and clearer; (2) Learners' expectations and responsibilities should be clearly established within the online environment (requirements, deadlines, ethical rules, etc.); (3) Synchronous and asynchronous discussions should be provided for learners while learning; (4) Activities should allow learners to provide balanced amount of personal and impersonal information; (5) Online environments should support learning experiences based on facts and information (e.g., real world examples) as well as those developing concepts and theories; (6) Online learning activities should stimulate exploration and decision-making features within learners; and, (7) Working groups in online learning environments should be studied previously. In particular, mixed groups of introvert and extrovert learners can increase their success rate. As a result, the learner's personality can affect the learning behavior, learning style and the preferred learning activities in CBL. In particular, some personalities would prefer posts and asynchronous discussions while others would be more active and prefer social interactions. Furthermore, some personalities would prefer working in groups with a partner having an opposite personality.

Moller and Soles (2001) proposed the learning content, methods and the learning style for each personality trait identified in MBTI in order to enhance distance learning performance. For example, Extrovert-Intuitive learners prefer auditory learning style and they should use videoconferencing, collaborative learning activities and problem-solving case studies. Introvert-Sensing-Thinking learners prefer visual learning style and they should use computer based instruction, video conferencing and synchronous or asynchronous learning activities. Hence, the learner's personality can influence the preferred learning content and the followed learning style in CBL.

Daughenbaugh, Ensminger, Frederick, and Surry (2002) showed that extrovert and intuitive learners prefer online courses more than introvert and sensitive learners. In particular, extrovert learners enjoyed synchronous and asynchronous computer-mediated communication. This study highlighted that the learner's personality can affect the adoption of CBL in general and the provided learning activities in particular.

Barkhi and Brozovsky (2003) showed that feeling type of learners preferred rich communication modes (emails and audio-video) which affected positively their learning performance. Hence, the learner's personality can affect the adoption of the communication modes to learn in CBL.

Bishop-Clark, Dietz-Uhler, and Fisher (2007) showed that extrovert learners performed better than introvert learners in distance learning; however, they were both satisfied with this learning experience. Learners who are feelers felt more isolated from their friends and teachers than thinkers. Besides, they spent less time on the course, felt unsatisfied and were not willing to recommend the course to other learners. Sensors felt isolated as well within the distance learning experience and spent more time on the web looking for answers rather than learning, while intuitive learners were motivated and satisfied with this learning experience more than face to face learning. Finally, no significant difference related to the performance or satisfaction of an online course was found for the judging/perceiving dimension. This study highlighted that personality can affect the learner's satisfaction and performance level in CBL.

Kim, Lee, and Ryu (2013) showed that width-first instructional strategy made introverted learners as good as extroverted learners using the breadth-first strategy. Thus, the learner's personality can affect the preferred instructional design of a given CBL system.

Bolliger and Erichsen (2013) proved that the learners' personalities can affect the learners' satisfaction in the learning environments (online and blended) and the learning activities defined within them, namely communication modes and learning style. In particular, the learner's personality defined how each learner preferred to communicate with others (friends or teachers) and how to learn (alone or in groups). Bolliger and Erichsen (2013) showed, for example, that learners who are sensors were more satisfied with using chat dialogue and working on their projects alone than intuitive learners in online courses. Hence, the learner's personality can affect the preferred communication modes and the followed learning style (alone or in groups) in CBL.

Irani et al. (2003) showed that extrovert learners had a significant degree of perception related to the used instructional techniques to deliver the course, course management, social interaction acceptance and grades. Introvert learners, however, had a significant degree of perception related to the used instructional techniques and course grades only. Hence, the learner's personality may affect how learners perceive their CBL experience when it comes to specific types of learning activities.

Based on the studies presented above, the learner's personality can affect how learners prefer the learning content and the learning approach, recollect information, communicate, behave, act and perform. Besides, it is the one which defines the level of adoption of a particular CBL system.

5. Discussion

In this study, a comprehensive literature review found only nineteen research works which incorporated personality in CBL. Al-Dujaily et al. (2013) also identified that very few studies have focused on the relationship between personality traits in CBL. Besides, despite the recent attention that other emerging approaches, such as flipped classroom, augmented reality, edutainment and educational games are gaining due to their features that can make them very efficient in delivering learning contents to the students (Tlili, Essalmi, & Jemni, 2015; Bishop & Verleger, 2013; Chang, Morreale, & Medicherla, 2010; Corona, Cozzarelli, Palumbo, & Sibilio, 2013; Huang, Huang, & Tschopp, 2010; Jong, Shang, Lee, & Lee, 2010), none of those current studies have investigated the importance of the learner's personality in them. This may be because these approaches are more complicated than designing e-learning systems. For example, Koster (2004) stated that game design is not an easy task since it is not a precise science. Dunleavy and Dede (2014) highlighted that Augmented Reality (AR) experience is difficult for learners, teachers and designers. Therefore, an investigation on how personality differences can affect these learning approaches is needed.

Furthermore, the presented studies used an explicit method (i.e. the learners already know that the instructor is assessing them), namely questionnaire, to identify the learner's personality. Questionnaires usually present statements that define individuals. The individual has to select the answer or statement that best describes his/her qualities or characteristics. However, individuals can have low self-knowledge, which may not allow them to answer the questionnaire correctly (McDonald, 2008). Besides, questionnaires are typically too long and can make individuals stressed and not motivated. Moreover, questionnaires may not be the best method to ask people about themselves, since people try to respond in a fashion that they perceive as being more acceptable, when they feel they are assessed by others (Okada & Oltmanns, 2009).

To overcome this problem, it is possible to use some implicit methods to model the learner's personality based on his/her traces kept in the e-learning environment (Campos, Alvarez-Gonzalez, & Livingston, 2012; Romero & Ventura, 2006). For example, these traces can be the time spent interacting with the learning content or the number of clicks. For instance, Halawa, Shehab, Hamed, and Essam (2015) modeled the learner's personality based on his/her behavior within a Learning Management System (LMS) and Facebook. In this context, Learning analytics (LA) has emerged as a very promising area with techniques to effectively use the data generated by the learners while learning (Aljohani & Davis, 2012), which can provide information about the learners' behavior. Thus, to enhance the computer based learning experience by providing an adaptive learning based on personality, it is possible to use LA where the learner's personality is identified and the learning process is personalized based on individual learner's personality. In this context, during the learning/playing process, the learners' generated data are collected and stored in an external server (e.g., SQL server). Depending on the volume of data traffic generated, the server should be able to manage quite high workloads efficiently. Then, the learners' data is fed to a learning analytics system which applies various data mining algorithms (e.g., Naïve Bayes algorithm) to identify each learner's personality deriving from personal behavior patterns logged in the collected data. Fig. 3 proposes an approach to identify the learner's personality using LA. A learner with an unidentified personality gets involved in computer based learning. Meanwhile, the system collects and stores the learner's data and traces where LA techniques are applied to identify the learner's personality. Finally, and after identifying the needed variables for the personalization process from the model presented in Fig. 1, the computer based learning is adaptable to the identified personality.

6. Conclusion, limits and potential future directions

Investigation of the learner's cognitive styles in computer based learning is still a new area. In particular, very few studies have focused on investigating how personality differences can affect learners' learning experiences in computer based learning. This paper presents a study regarding personality and computer based learning by conducting a comprehensive literature review of past studies, and discusses the implications of the findings.

The current study presents four new findings: (1) Personality is

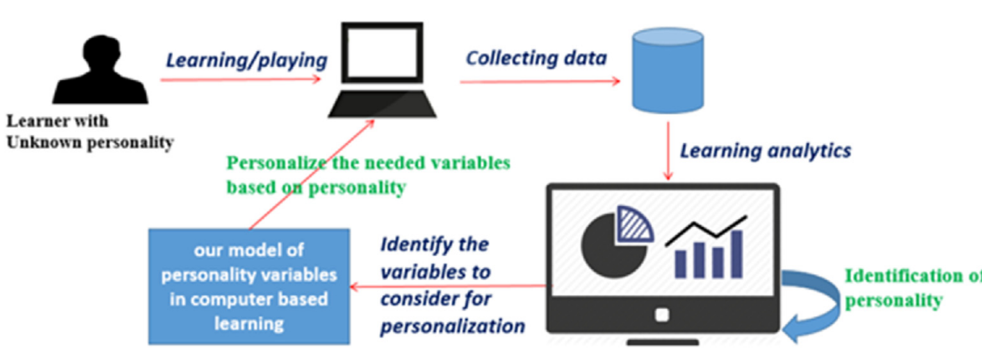

Fig. 3. Learning Analytics approach for adaptive computer based learning.

responsible for how a learner learns, communicates with others, recalls information, solves problems, takes notes, etc.; (2) Many personality variables are found which researchers and practitioners should consider for providing an adaptive computer based learning. These variables can be within learners themselves, such as feelings and behavior, or within the given learning system, such as user interface design, provided learning strategies and communication modes (see Fig. 2); (3) The MBTI model is the most referred model in the literature for identifying the learner's personality in CBL; and, (4) A new approach for computer based learning systems is presented by referring to implicit methods using learning analytics instead of questionnaire-based approach to provide an adaptive CBL based on personality.

The current study, while providing some crucial insights for improving learning experiences in computer based learning, has a number of limitations. For example, the review process was limited by the search keywords and terms used. This can limit the number of obtained studies. The study is based purely on the findings from the literature review and is not guided by any experimental setup. Despite these limitations, this study has provided a solid ground to investigate how personality affects computer based learning and what personality variables should be considered by researchers and practitioners to provide an adaptive CBL.

Future research should not only validate these results through empirical studies but should also consider emerging approaches to learning. For example, the number of people playing games on computers or mobile devices is increasing and a number of games based learning approaches and edutainment environments are emerging as a result. Future research is therefore needed to investigate how personality differences may affect learners' experiences while learning and being entertained through educational games. This could be done by investigating the game elements that interest each personality trait and the followed game-playing style. In this context, it is possible to refer to expert systems as a method to identify the learners' personalities based on their game traces. These traces are considered as the input for the expert system. Besides, another set of data, which is the knowledge base, is prepared by the experts (psychologists). It contains classification rules which support the assignment of each learner based on his/her collected traces to a specific class, such as introvert or extrovert. The expert system inference engine is then used to identify the learners' personalities (based on the input traces and the prepared classification rules). Finally, the designed educational game is adapted based on the obtained personality results of each learner. For example, extrovert people are more risk takers than introvert people (Walsh, 2012). This could be used in educational games by redirecting extrovert learners to game paths where various game enemies are implemented while introvert learners will be redirected to safe game paths. Similar research could also help to improve learning experiences of the learners in other emerging approaches, such as virtual reality based learning, augmented reality based learning, ubiquitous learning scenarios, and so on. For instance, in virtual and augment reality, collaborative learning activities can be personalized according to the leaners' personalities (i.e. the learner is assigned to a group having a similar/opposite personality to his/her personality).

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