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A survey of personality and learning styles models applied in virtual environments with emphasis on e-learning environments

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Abstract Today, one of the most important and challenging issues in artificial intelligence is modeling human behavior in virtual environments. Furthermore, studying e-learning environments is in great demand in computer science which requires understanding human behaviors. Thus, considering human behavior factors, such as personality, mood, and emotion, and modeling them in e-learning environments is a challenging issue in artificial intelligence. The purpose of this paper is to review the psychological models of personality used in computer science. In addition, the most important applications of personality models and their direct related topics in learning, i.e. learning style issues in e-learning environments, are presented. The study shows that researchers tend to use models that are simple to implement in virtual world and are as comprehensive as possible to cover all the features of human behavior. Finally, we concluded that models such as the Five Factor Model, the Myers–Briggs Type Indicator personality model, and Felder–Silverman learning styles model have the two most important features, which are simplicity and comprehensiveness. These two features have made these psychology models the most favorable in the virtual world.

Keywords Human computer interaction · Personality · Learning styles · E-learning environments · FFM · MBTI · Felder–Silverman

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1 Introduction

One of the dreams of artificial intelligence is designing machines which would be able to behave more human-like. To accomplish this goal, it is necessary to understand the ways, in which humans perceive and understand the world. Understanding these ways assists us in developing computers that are more advanced in interacting with humans. This would lead researchers to find answers to questions such as "is it possible for computers to experience emotions and mood, or to have personality similar to human beings?" In two recent studies (Zeng et al. 2009; Trabelsi and Frasson 2010), the researchers tried to identify and track users' behaviors, particularly affective behaviors, which enables machines to understand users' needs and react to them accordingly (Trabelsi and Frasson 2010).

E-learning environments, which are highly demanded in computer science, require understanding human behaviors. Since e-learning environments usually lack the necessary attractions and the dynamic characteristics of the face-to-face learning setups, developers need to concentrate on designing interactive user interfaces based on user's cognitive factors. Considering personality, emotions, and individual differences in e-learning systems, improves learning and increases learners' motivation, joy, and involvement (Latham et al. 2012). In this paper, we have focused on evaluating several personality models, which are used in virtual environments. The study would help the researchers to choose the appropriate models for their studies.

In this paper, Sect. 2 explains the psychological background of personality theories along with learning styles models. In Sect. 3, we present the use of personality theories in computer science. Section 4 discusses the e-learning environments that used learning style models. Finally in Sect. 5, conclusions and implications are presented.

2 Psychological principles

2.1 Personality

Several definitions have been presented to define personality. Schultz and Schultz (2009) defined personality as the internal and external aspects of individual characters that affect the human behaviors in different states. Hartmann (2006) believes that personality comprises thoughts, feelings, desires and behavioral tendencies that exist in every person.

Psychologists have presented different views of personality based on their research approach. At the end of the 19th century, Sigmund Freud expressed that personality can be divided into three levels: the preconscious, the conscious, and the unconscious. Later, he revised his theory and introduced another view of personality through three parts, i.e. Id, Ego and Superego (Schultz and Schultz 2009).

After that, Carl Jung, who worked with Freud in the early stages of his career, presented a different view of the personality. He believed differences among human behaviors are quite regular and stable. Also, he believed these differences originate from various ways that individuals understand and make their decisions (Dewar and Whittington 2000; Vincent and Ross 2001). Furthermore, he proposed that personality consists of independent substructures that influence each other. He introduced the substructure which includes personal, unconscious, and the collective unconscious (Schultz and Schultz 2009). Finally, Jung presented eight psychological types based on two attitudes and four functions.

Table 1 Dimensions of personality and learning style models

MBTI	*Felder–Silverman*
Extroversion/introversion	Sensory/intuitive
Sensing/intuition	Visual/verbal
Thinking/feeling	Active/reflective
Judgment/perception	Sequential/global
Five factor model	*Eysenck model*
Extroversion	Extroversion
Agreeableness	Psychoticism
Neuroticism	Neuroticism
Conscientiousness	
Openness	
16 PF Cattell	*Minnesota multiphasic personality inventory*
Warmth (A)	Hypochondriasis
Reasoning (B)	Depression
Emotional stability (C)	Hysteria
Dominance (E)	Psychopathic deviate
Liveliness (F)	Masculinity/femininity
Rule-consciousness (G)	Paranoia
Social boldness (H)	Psychasthenia
Sensitivity (I)	Schizophrenia
Vigilance (L)	Hypomania
Abstractedness (M)	Social introversion
Privateness (N)	
Apprehension (O)	
Openness to change (Q1)	
Self-reliance (Q2)	
Perfectionism (Q3)	
Tension (Q4)	
VARK	
Visual	
Aural	
Reading	
Kinesthetic	

Adler, who was an Austrian psychotherapist, believed in a theory of three life tasks: occupation, society, and love which are engaged with each other. Based on this theory, he introduced four types of personality: dominant type, getting type, avoiding type, and socially useful type (Schultz and Schultz 2009).

Cattell et al. (1970) extracted 16 factors as the main factors that exist in the human personality. He called these factors "source traits", because he thought that they provide the original source of the surface which is considered as personality. This theory is known as "the 16 personality factor model" (Table 1). It uses the 16PF questionnaire to measure these factors (Schultz and Schultz 2009).

Eysenck created several questionnaires to apply in his studies and proposed personality theory that is based on three dimensions: extraversion versus introversion, neuroticism versus stability, and psychoticism versus socialization (Table 1; Schultz and Schultz 2009).

In 1992, Robert R. McCrae and Paul Costa introduced the Five Factor Model (FFM) of personality theory. The factors are extraversion, conscientiousness, neuroticism, openness, and agreeableness (Table 1; McCrae and John 1992).

In summary, personality includes the aspects of individual differences that affect the human behaviors in different states. Moreover, there are many personality models to classify people based on their individual differences. In learning domains, personality and individual differences among people are called learning styles. In the following section, the most frequently used learning style models are reviewed.

2.2 Learning styles

Psychological studies indicate that people have many individual differences in decision-making, problem solving, and learning processes. The individual differences in the learning process, i.e. the differences in understanding, evaluating, and processing information (Li et al. 2007; Yeung et al. 2005), are called learning styles (Logan and Thomas 2002). There are similar definitions such as the Keefe's definition of the learning style which states "Learning style includes cognitive, emotional, and physiological features, which are used to recognize how the learner understands the concepts and interacts with the learning environment" (Logan and Thomas 2002).

The learning styles show preferences and priorities of the individuals in the learning process (Dewar and Whittington 2000; Durling et al. 1996). For example, individuals who have good visual memory and weak verbal ability prefer learning materials to be presented to them visually rather than verbally. That is why teachers have to consider these differences and present the learning contents according to learners' learning styles. It should be noted that Griggs believes that there is no relationship between learning styles, intelligence, mental ability, and learning efficiency. Also he believes that there is no superiority among learning styles.

It should be noted that if learning contents are presented to learners without considering their preferences and learning styles, the learning process would be disrupted (Abrahamian et al. 2004; Durling et al. 1996). Thus it is important to consider the learning styles in the learning process. Although teachers, in traditional classrooms, try to match the content with learners' learning styles as much as possible, this is difficult in e-learning environments in which face-to-face interaction is missing. That is why researchers proposed several learning style models which can be used in e-learning environments.

2.2.1 Instruments used to determine the Learning style of a user

There are many instruments that classify individuals based on their learning styles. For example, Kolb (1985) introduced Kolb's learning style inventory which is based on Kolb's learning cycle theory which consists of four stages: Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE). If learners finish a cycle, learning occurs.

Honey and Mumford (1986) developed a questionnaire based on Kolb's Cycle theory. Their questionnaire has 80 questions and classifies individuals into four groups: Activist, Theorist, Pragmatist, and Reflector. Each group is related to one of the stages in Kolb's cycle (Logan and Thomas 2002).

Another questionnaire is GRSLSS that was created by Grasha and Richmann. This questionnaire has 60 questions and categorized individuals into six groups: competitive, Collaborative, Avoidant, Independent, Dependent, and Participant (Lang et al. 1999; Logan and Thomas 2002).

Felder–Silverman Learning Style Index and model (1988) was proposed considering four dimensions for the learning styles: Active/Reflective, Visual/Verbal, Sensing/Intuitive and Sequential/Global (Table 1).

Fleming (2006) introduced VARK learning style model which has been modified from VAK model (Barbe et al. 1988). The VARK learning style model categorizes learners to four groups which are: Visual (V), Aural (A), Reading (R), and Kinesthetic (K).

Also, Isabel Briggs Myers and Kathrin Briggs proposed a questionnaire called MBTI (Myers–Briggs Type Indicator), which was based on the Jung's personality theory (Schultz and Schultz 2009). At the beginning, MBTI was used for business sciences, but nowadays it is also used for educational purposes (Schultz and Schultz 2009). According to the Center for Applications of Psychological Type, MBTI is the most commonly used personality inventory in history; approximately 2,000,000 individuals use MBTI for their personality detection every year. Moreover, the validity of the MBTI model has been widely recognized (Kim et al. 2013). That is why MBTI is a powerful tool to determine the learning styles of learners.

Based on MBTI, each person has instinctive preferences that define his/her behaviors in different situations (Dewar and Whittington 2000). MBTI uses four two-dimensional functions based on the Jung's theory (Table 1). The Jung's theory specifies three functions: Extraversion/Introversion (E/I), Sensing/Intuition (S/N) and Thinking/Feeling (T/F). Myers–Briggs added another dimension to the Jung's typological model, i.e. Judging/Perceiving (J/P) (Abrahamian et al. 2004; Rushton et al. 2007).

2.3 The relationship between personality and learning styles

As mentioned above, the learning style definition is close to the personality definition. In fact, it is believed that a learner's learning style depends on his/her personality, hence individuals with different personalities have different learning styles (Yeung et al. 2005). In 1996, Furnham found out a relationship between Kolb's learning styles and Eysenck personality theory (Sadler-Smith 2001). Also, Eysenck showed that there is a relationship between personality traits and learning styles (Zhang 2001). Drummond and Stoddard reported that learning styles are related to cognitive factors. Also, Jakson and Jones (1996) explained that there is a relationship between at least one of the personality traits and learning style dimensions. Additionally, Furnham and Jackson clearly expressed that the learning style of an individual is a subset of his/her personality (Furnham and Jackson 1999). That is why many researchers use personality models interchangeably with learning styles in learning environments.

Based on the importance of the personality, which is closely related to the learning style in e-learning environments, we have surveyed a set of widely used personality models which are used in e-learning environments.

3 Using the personality models in virtual environment

In recent years, many studies in the field of psychology, neuroscience, philosophy, and cognitive science have been carried out to model human behavior. Figure 1 shows the number of

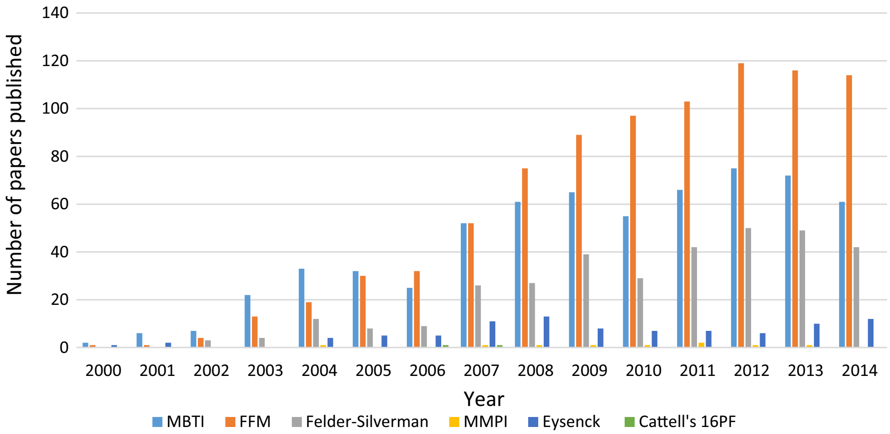

Fig. 1 Research trends based on psychological personality models in e-leaning environments

papers published over the past 15 years related to personality models and e-learning environments. It shows an increasing trend in the use of three models, while the rest have been used less frequently. It should be noted that we used the keywords such as e-learning, personality, learning style and names of personality model in google scholar to plot Fig 1.

In this section, the most important models in personality modeling are listed. We categorized them into two general groups: the related studies based on psychological models, and the studies that are not based on any specific psychological model.

3.1 Related studies based on psychological models

Shortly after the appearance of artificial intelligence, the application of cognitive and psychological models in computer science expanded greatly. This expansion began by using psychological models which had the potential to be implemented in computers. In this section, the studies related to the most used models are listed (Table 2).

3.1.1 The five factor model

Ball and Breese (1998) modeled emotions and personality in intelligent agents using Bayesian Belief Networks (BBN). They used two dimensions of the personality: dominance and friendliness. In addition, they used FFM for personality and the OCC (Ortony et al. 1990) model for emotion modeling, in which a character-based user interface is implemented. It is based on speech recognition and speech generation, which enables it to identify a user's emotions and personality. Also, the user interface generates appropriate behaviors by an automated agent in response to users' interactions.

André et al. (2000) presented a general framework that used personality and emotions to model different aspects of the affect in their designed user interface. They implemented their model in three scenarios: (a) a receptionist agent in an information system, (b) a seller agent in a virtual market place, and (c) a farmer agent in a farmyard. The authors applied the OCC model for emotion modeling and FFM for personality modeling. They used the extraversion and agreeableness dimensions of FFM to simulate personality (Kshirsagar and Magnenat-Thalmann 2002; Vinayagamoorthy et al. 2006). Furthermore, they simulated four emotions: sadness, happiness, fear, and anger.

Table 2 Related works based on psychological models

Researchers	Personality	Mood	Emotion	Method	Application
Ball and Breese (1998)	FFM (Dominance and friendliness)	No	OCC	Bayesian belief network	Speech recognition and speech generation
André et al. (2000)	FFM (extraversion and agree-ableness)	No	OCC (sad, happy, fear and anger)	Modeling	Lifelike characters
Kshirsagar and Magnenat-Thalmann (2002)	FFM	Good and bad	OCC + hate + surprise	Belief Beysian network	Chat system
De Rosis et al. (2003)	FFM	No	OCC	Agent modeling	Virtual human
Egges et al. (2003, 2004)	FFM	Yes	OCC	Computational methods	Conversational virtual humans
Mehdi et al. (2004)	FFM	Yes	OCC	Computational model	Virtual reality training tool for fireman
Chittaro and Serra (2004)	FFM	No	No	Probabilistic automata	Virtual characters
Poznanski and Thagard (2005)	FFM	No	Neutral, sad, happy, angry, afraid and curious	Artificial neural network, computational model	Video games
Moshkina (2006)	FFM	Positive and negative	Yes	Computational model	Human-robot
Santos et al. (2011)	FFM	PAD	OCC	Computational model	Group decision-support systems
Karimi and Kangavari (2012)	FFM (neuroti-cism)	No	No	Computational model	Virtual soccer
Hwang and Lee (2013)	FFM (extra-version)	No	No	Fuzzy cognitive map	Animatronic pet dinosaur toy (Pleo)
Dang and Duhau (2008, 2009)	MBTI	No	Combined OCC and Lazarus and Scherer theory	Modeling	Robotic
Lee et al. (2012)	MBTI	No	No	Artificial neural network and genetic algorithms	Genetic robot on mobile phones
Orozco et al. (2011)	MMPI	Yes	Yes	Linear modeling	Virtual humans
Fatahi et al. (2015a)	MBTI	No	OCC	Computational model	E-learning

Egges et al. (2003) introduced a generic model of personality, mood, and emotions. They used their model to design conversational virtual humans. The authors applied the OCC model for emotion modeling and FFM to model personality. In 2004, Egges et al. improved their model. The new model can linearly update the emotion, mood, and personality factors. Consequently, they showed how their model can be integrated with an application such as an expressive MPEG-4 talking head with speech synthesis.

De Rosis et al. (2003) implemented a 'realistic' 3D embodied agent, which can be animated in real-time, called Greta. Greta was made up of three interrelated components: a representation of the agent mind, a communication component, and a face expression component. The affective components, which are personality and emotions, were located in the agent's mind component. The components simulated how emotions are triggered and decay over time based on the agent's personality. FFM and OCC are used to model personality and emotions respectively.

Mehdi et al. (2004) attempted to develop a model that comprises emotion, mood, and personality factors. They used the OCC model for emotion modeling and FFM for personality modeling. In this study, personality was considered as a parameter that defines the threshold of the appearance of emotions and mood as a filter for moderating the intensity of the emotions. At the end, they implemented their model in a virtual reality training tool on a fireman agent for enabling him to behave similar a human fireman.

Kshirsagar and Magnenat-Thalmann (2002) designed a layered model of the human personality, mood, and emotion. They modeled personality using Bayesian Belief Networks. They described personality using FFM and emotion using OCC. In addition, they added hate and surprise to the OCC model. Kshirsagar and Thalmann considered two types of mood: good and bad. The model had been integrated in a chat system such that its virtual agent can have different personalities and moods.

Chittaro and Serra (2004) presented a goal-oriented method for agent modeling. The agents' behaviors determined probabilistically based on their personality, which are based on the FFM model, and their goals. This research focuses on the idea that personality has a probabilistic influence on behavior rather than a deterministic one.

In 2005, Poznanski and Thagard modeled personality and its changes through Artificial Neural Network (ANN). They proposed a novel computational model of personality and its changes over time, called SPOT (Simulating Personality over Time). SPOT has four basic components: personality, emotions, inputs describing the situations, and behavioral outputs. The model was used in a video game called Sims, and its ultimate goals were to help understand personality and create virtual characters that behave like human. SPOT used the FFM model in the personality component. The six basic emotions used in the SPOT's emotion component are neutral, sad, happy, angry, afraid and curious.

Moshkina (2006) presented an integrative behavior framework for affective agent called TAME. TAME combined personality traits, attitudes, mood, and emotions to generate affective behaviors. The personality component used FFM to simulate personality traits. Moshkina considered direct or inverse influence of personality on emotion generation behavior. In addition, she implemented the mood module based on two types: positive and negative mood. Finally, Moshkina evaluated the TAME framework into a human-robot application.

Santos et al. (2011) used artificial intelligence agents who have personality, mood, and emotions in a group decision-support system study. Group decision-support systems are interactive computer-based environments that support team efforts to complete joint tasks. In this research, the cognitive factors in decision making processes were formulated. The goal of this research was to improve the negotiation process through argumentation using the affective characteristics of the involved participants. The main idea in this research was to select the best decision in negotiation process. Santos and his colleagues used FFM, PAD,[1] and OCC psychology models for personality, mood, and emotion simulation respectively.

Karimi and Kangavari (2012) proposed a computational model of personality called Personality Integrated ACT (PIACT). This model is an extension of ACT-R cognitive architecture to consider the personality factors. The model is based on the anxiety trait, which is a facet of the neuroticism dimension of FFM. The model was evaluated in a simulated soccer environment. The results signified a decrease in the efficiency factor of the goalkeeper, due to an increase in the number of the scored goals. Consequently, the agent's performance decreased when its anxiety increased.

Hwang and Lee (2013) focused on analyzing users' behavior through considering personality. They used the Fuzzy Cognitive Map (FCM) modeling to create a system which can better interact with a user based on his/her personality. Their system was Pleo, an animatronic pet dinosaur toy, which can interact with users. The authors focused on two measures: the users' degree of extroversion, as the users' personality trait from FFM, and the users' interaction with Pleo, as the users' behavior. The results show that the proposed FCM-based approach helps to predict users' personality and adjust Pleo's personality to match the user's personality. They concluded that personality matching between users and devices would increase users' satisfaction level.

In recent years, social networks have grown significantly as a new medium of human-computer interaction. Therefore, there are many studies on the relationship between activities on social networks and personality traits (Sumner et al. 2011; Moore and McElroy 2012), in which FFM is used. Their results show that there are significant correlations between a set of an individual's personality traits and his/her Facebook activity. Finally, their results prove that Facebook activity provides limited clues to an individual's personality.

3.1.2 MBTI

Dang and Duhau (2008) proposed a generic model of emotion in EmotiRob project. They combined the OCC model and Lazarus–Scherer theory, and used them in emotion component. Also, they used MBTI in their personality component. In this model, the authors considered the intensity of emotions based on personality types. In 2009, Dang and Duhau upgraded their model. They defined emotion as a process in the human body that began from sensing an event through the interpretation level, which takes into account the internal cognitive state. The process proceeds all the way down to the behavior part where the intensity of current emotions will be calculated. The human body is responsible to express the calculated intensities to outer world according to the personality type of an individual. They validated their model by designing a robot, called Generic Robotic Architecture to Create Emotions (GRACE), and asking a group of people to evaluate the personality of the robot. The results show that the people could detect different personality and emotions in GRACE.

Lee et al. (2012) created a genetic robot which has personality based on MBTI. The genetic robot uses ANN and Genetic Algorithms (GA) to behave similar to humans to become more believable for humans.

Fatahi et al. (2015a, b) proposed a computational model to calculate a user's desirability, generated by an event, based on personality traits in a simulated e-learning environments. Desirability is one of the most important factors in determining a user's emotions. The proposed model is evaluated for two groups of learners: performance motivational orientation (PMO) and mastery motivational orientation (MMO). The results for two groups of learners

[1] Pleasure, Arousal, and Dominance mood model introduced by Albert Mehrabian.

show that the proposed model formulates the relationship between personality and emotions with high precision.

3.1.3 MMPI

Orozco et al. (2011) presented an action selection mechanism to simulate the human behavior in a virtual human. The selection process was based on beliefs, desires, and intentions of the virtual human, which acts according to its personality. The Minnesota Multiphasic Personality Inventory (MMPI) was used to identify a system user's personality (Table 1). In this research, the emotional state and mood were updated linearly based on the virtual human's previous state.

3.2 Other related studies

There are studies in artificial intelligence literature that did not use any specific psychological model. Although, they have used psychological factors but they did not base the research within any specific psychological model. In this section, we have summarized these studies.

Ushida et al. (1998) proposed an emotion model for life-like agents. They employed a multi-module architecture in order to implement the interactions. Also, the model had a learning mechanism to diversify behavioral patterns. Ushida and his colleagues modeled personality for life-like agents based on emotional differences in humans. Finally, the results indicate that these agents are more believable to users.

Schmidt (2002) presented PECS (Physical conditions–Emotional states–Cognitive capabilities–Social status) model. He believed that human behavior is influenced by personality traits. Likewise, he emphasized there are many different physical, emotional, cognitive and social factors that influence the internal life of a human being, which he considered in his model. The PECS model is an architecture which provides a framework with spaces that can be filled by a user, according to the user's status and the problem at hand.

Wang and Liao (2011) proposed an adaptive e-learning system in teaching English language that considers learners' characteristics, such as gender, personality types (introverted, mildly introverted, neutral, mildly extroverted, and extroverted), and anxiety levels (low, moderate, and high anxiety). This e-learning system presents different levels of teaching content for vocabulary, grammar, and reading for learners with different characteristic combinations. The results showed that this personalized adaptive learning system improves student learning outcomes. The authors compared the results of their system with a regular online course. The results indicate that learning performance in this adaptive e-learning system is higher than a regular e-learning system.

4 Using the learning style models in e-learning environments

In this section, we survey learning style models in e-learning environments, which are summarized in Table 3.

4.1 MBTI learning style

Abrahamian et al. (2004) designed an interface based on users' learning styles. The main goal of this research was to provide a system that matches the content delivery with users' learning styles. The results of this study, in which MBTI test was used, show that designing content

Table 3 Related works using learning style models in e-learning environments

Researchers	Learning style	Emotion	Method	Application
Abrahamian et al. (2004)	MBTI	No	Experimental	Design user interface
Haron and Salim (2006)	MBTI (extravert/introvert and sensing/intuition)	No	Fuzzy logic techniques	Adaptive hypermedia learning system
Fatahi et al. (2008, 2009), Fatahi and Ghasem-Aghaee (2010a, b)	MBTI	OCC	Agent modeling	Virtual classmate agent, virtual teacher agent in English language learning
Bachari et al. (2010)	MBTI	No	Modeling	Intelligent tutoring system (LearnFit)
Niesler and Wydmuch (2009)	MBTI	No	Perdition	Intelligent tutoring system
Fatahi et al. (2015a)	MBTI	No	K Nearest neighborhood	E-learning
Yannibelli et al. (2006)	Felder–Silverman	No	Genetic algorithm	Online courses
Graf (2007, 2013), Graf et al. (2009)	Felder–Silverman	No	Perdition	Online courses
García et al. (2007)	Felder–Silverman	No	Bayesian networks	Web-based education system
Gong and Wang (2011)	Felder–Silverman	No	Perdition (SVM)	Virtual learning environments
Latham et al. (2012)	Felder–Silverman	No	Predicting learning styles through natural language dialogue	Conversational intelligent tutoring system
Rani et al. (2015)	Felder–Silverman	No	Ontology based	Web-based environment
Klašnja-Milićević et al. (2011)	Felder–Silverman	No	Hybrid recommendation strategy	E-learning
Du et al. (2005)	Cattell's 16PF	No	Modeling learner and data mining	Web-based environment
Chaffar and Frasson (2004)	Eysenck personality questionnaire	Yes	Emotional intelligent agent modeling, Naive Bayes classifier	Tutoring system
Rakap (2010)	VARK	No	Experimental	Web-based environment

delivery according to users' learning styles has a significant effect on learning process. Furthermore, the results indicate that users prefer user interfaces designed based on their learning styles.

Haron and Salim (2006) proposed a framework for individualizing the learning contents in adaptive learning systems. The framework used fuzzy logic techniques and MBTI to model users' learning styles. He considered just two dimensions of MBTI: extrovert/introvert and sensing/intuition. Haron et al. evaluated the model in an e-learning environment for a group of students in the computer science field. The results confirm that students learn more effectively when they are taught with methods that are matched with their learning styles.

Ghasem-Aghaee et al. (2008) designed an intelligent agent in a computer-based learning environment. Their improved learning environment was more enjoyable and believable to learners. Also, Fatahi et al. (2008) and Fatahi et al. (2009) designed a model based on learners' learning style which was based on MBTI. They used an expert knowledge-based system to select a suitable Virtual Classmate Agent (VCA). Their expert knowledge-based system used MBTI to select suitable VCA for a learner. The VCA selected tactics to interact with the learner and was able to cooperate intelligently with the learner. The results indicate that the presence of VCA leads to improvement in the learning process and attractiveness of their virtual learning environment. In 2010, they combined their models and proposed a new model (Fatahi and Ghasem-Aghaee 2010a, b). The new model used two agents with personality and emotional filters: Virtual Teacher Agent (VTA) and Virtual Classmate Agent (VCA). VTA used a teaching style appropriate for a learner based on the learner's learning style. VTA proposed a suitable VCA to the learner based on a situation at hand. VCA was an intelligent agent and had its own learning style. Finally, the results show that considering the human behavior factors in interaction with the learner and the presence of the intelligent agents, with human-like features, improves learning rate and satisfaction level of learners.

Bachari et al. (2010) proposed an adaptive e-learning model based on learners' personality called LearnFit, which works based on the MBTI personality model. It was able to match the system's teaching style to a learner's preference in online distance education. Bachari, et al. developed modules to determine a learner's learning preferences and to select a suitable teaching strategy for learners. The results show that placing the learner in an environment according to learner's preference in e-learning education leads to progress in learning process and would make the e-learning environment more enjoyable.

Niesler and Wydmuch (2009) studied adaptive user profiling, based on learning predispositions. They used MBTI for modeling learners' preferences. They believed that learning preferences change over time. Thus their model considers time-related changes in the learning preferences.

Fatahi et al. (2015c) tried to find a set of features which are important in determining users' learning style automatically. They used MBTI learning style questionnaire as their ground truth. The results show that several features can be used to predict learning styles with high precision.

4.2 Felder–Silverman learning style

Felder–Silverman learning style model is the most frequently used model in the computer science research. Focusing on Felder–Silverman learning style, Yannibelli et al. (2006) used a genetic algorithm approach to recognize students' learning styles. This algorithm identifies students' learning styles based on their actions while attending an academic course. A genetic algorithm help to explore all the possible combinations of actions with the aim of identifying which combination is preferred by a student attending multiple academic units. Also, the authors believed that students' learning style changes over time. Their proposed genetic algorithm can detect learners' learning styles with high accuracy.

Graf (2007), in her PhD thesis, proposed a general framework to predict learning styles of learners. In her framework, learning materials presented to the learners based on the detected learning styles. She used Felder–Silverman learning style model to identify learning styles, based on the behavior and actions of learners. The results show that considering learners' learning styles increase performance of the learners. Also, Graf et al. (2009) studied learners' behavior according to Felder–Silverman learning styles model. The results indicate that learners with different learning styles have different behaviors. She proposed that researchers can use the results of this study to design adaptive e-learning systems.

García et al. (2007) used Bayesian Belief Networks to detect the learning style of a learner in a Web-based educational system. The estimated learning styles using the BBN approach was compared to the Felder–Silverman questionnaire results, which showed high precision in determining the perceptual style of students.

Gong and Wang (2011) believed that learning styles are dynamic and change over time. They used Support Vector Machine (SVM) to identify a user's learning styles in a virtual learning environment based on Felder-Silverman learning style model.

Klašnja-Milićević et al. (2011) also used Felder–Silverman learning style to develop Protus (Programing Tutoring System). Protus considers the pedagogical aspects of a learner, including his/her learning style, to recommend sequences of learning activities.

Latham et al. (2012) proposed a generic method and architecture for developing a novel conversational intelligent tutoring system (CITS) called Oscar. It leads a tutoring conversation and dynamically predicts and adapts to a student's learning style. Oscar acts as a human tutor and it answers learners' questions according to their learning styles. Also, Oscar can detect learning styles of learners with an accuracy between 61 and 100 %. The results indicate Oscar's tutoring was effective in improving the average learning rate of learners.

Graf (2013) presented an adaptive mechanism in e-learning systems which tries to present learning materials to learners according to their learning styles. The learning styles are detected automatically and dynamically by gathering data about students' behavior.

Rani et al. (2015) proposed an ontology-driven system which used Felder-Silverman learning style model. The ontology is used to provide personalized learning materials for learners. The authors used software agents to monitor learners' behavior and capture changes in learners' learning style and store this information based on the proposed ontology. A questionnaire, which measures different dimensions such as learner, teacher, course, technology, and design dimensions, was used to evaluate the system. The results show that the average score that was calculated for all dimensions is reasonable.

4.3 Cattell's 16PF questionnaire

In 2005, Jin Du and his colleagues (Du et al. 2005) tried to model learners based on three factors: personality, motivation, and strategy. Their model includes two parts: the static part based on the personality model and the dynamic part modeling behaviors. They used Cattell's 16PF questionnaire to model learners' personality. Also, the authors extracted relationship between behavior and personality of learners with data mining techniques such as Apriori algorithm. The model was trained based on learners' behaviors, and was evaluated in a web-based environment.

As it was mentioned before, it should be noted that in this study, and many other listed studies in this paper, the authors did not explicitly mention learning style and personality is used as a learner's learning style.

4.3.1 Eysenck personality questionnaire

Chaffar and Frasson (2004) developed an emotional intelligent agent. The agent's architecture includes three modules: The perception module, the control module, and the action module. This agent recognized the current emotional state of a learner according to his/her choice of a sequence of colors. After that, the agent identified the optimal emotional state for learning according to learner's personality. In this research, Naive Bayes Classifier was used to predict optimum emotional states. Moreover, the Eysenck personality questionnaire was used to identify a learner's personality.

4.4 VARK questionnaire

Rakap (2010) investigated the influences of individual differences, e.g. learning styles and computer skills of learners on knowledge acquisition in an online course by using the VARK learning style questionnaire. The experiment was conducted on forty six learners and the results support research hypothesis. The obtained results show that learning styles had significant effects on adult students' knowledge acquisition, and there is a moderate positive correlation between computer skills and students' success.

5 Conclusion

In this paper, we reviewed several personality models used in computer science. First, we surveyed psychological views about personality and learning styles. After that, we discussed the relationship between personality and learning styles. Since one of the most important applications of computers is in e-learning, we divided the survey in two sections: personality models used in computer science, and learning style models used in e-learning environments. In the review of the personality models, used in computer science section, two categories are used: related studies based on specific psychological models and related studies not using usual psychological models. Reviewing previous studies showed that FFM, MBTI, and MMPI are used in computer science to model human behaviors. The most widely used models are FFM and MBTI.

We also surveyed various learning style models used in e-learning environments such as MBTI, Felder–Silverman, Cattell's 16PF, and Eysenck. As shown in Fig. 1, MBTI and Felder–Silverman are used more often than the others, since they have more number of dimensions such as extroversion/introversion, sensory/intuitive, and visual/verbal. This would makes them suitable to be implemented in e-learning environments. Although 16 PF Cattell's and MMPI have many dimensions, however, they cannot be easily mapped into e-learning environments. For example, depression and paranoia dimensions, in MMPI, are more towards clinical symptoms and aspects of personality which are not suitable to be implemented in e-learning environments. Also, warmth and reasoning in 16 PF Cattell's are not easily detectable in such environments. Another example can be the emotional stability dimension which cannot be easily determined from an interaction log in an e-learning environment.

On the other hand, models such as Eysenck model have very limited dimensions, e.g. three in case of Eysenck's model. Furthermore, while the extroversion dimension is related to users' interaction styles in e-learning environments, the psychoticism and neuroticism dimensions are not very related and cannot be easily implemented in them. That could be the reason for Eysenck model not being used as much as MBTI, Felder–Silverman, and FFM. It should be noted that extroversion, agreeableness dimensions of FFM are simple to be implemented in virtual world. That could be why it is used more than Eysenck, 16 PF Cattell's and MMPI models.

It seems that the simplicity and comprehensiveness are the two features that make FFM, MBTI, and Felder–Silverman models more appropriate to be used in e-learning environments.

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