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Review Article

# Categorizing E-Learner Attributes in Personalized E-learning Environments: A Systematic Literature Review

Mohammad Hassan Abbasi[1], PhD Candidate; Gholam Ali Montazer[2*], PhD; Fatemeh Ghorbani[3], MSc; Zahra Alipour[4], PhD

[1]*Department of Information Technology Management, School of Management, North of Tehran, Islamic Azad University, Tehran, Iran*
[2]*Department of Information Technology Engineering, Tarbiat Modares University, Tehran, Iran*
[3]*Department of Industrial Engineering, Islamic Azad University, Tehran, Iran*
[4]*School of Management, Islamic Azad University, Tehran, Iran*

## ABSTRACT

**Background:** The development of learner models in learning management systems is among the most significant steps in designing personalized e-learning environments. The primary purpose of this modeling is to extract user characteristics in order to personalize the learning process based on learners' needs, learning style, personality, and individual circumstances.

**Methods:** The present study provides a review of published literature over the past 20 years in academic databases including IEEE, Sciencedirect, Wiley, and Springer. The search was limited to the studies on the personalization of e-learning environments based on learner characteristics, specifically the ones providing a reliable method for integrating these characteristics, as appropriate input variables, in the design of personalized e-learning systems.

**Results:** This study proposed a new method of classifying the learner characteristics as the variables for designing a personalized e-learning system. A total of 111 papers were considered for analysis. In the end, 22 influential learner characteristics were extracted and classified into six subcategories, namely cognitive, motivational, behavioral, emotional, metacognitive aspects, and combined domains. The proposed classification method was also compared with available related categorizations to demonstrate this method's advantage in designing a personalized e-learning environment.

**Conclusion:** The findings represent the learning criteria that can be utilized in designing adaptive learning systems. Moreover, it can also aid other researchers in this field to achieve a better perspective in learner modeling. Applying these characteristics as input design variables in personalized e-learning systems can result in a better solution for personalization.

**Keywords:** E-learning, Learner characteristics, Learner model, Personalized learning

**Corresponding author:*
Gholam Ali Montazer,
Department of Information Technology Engineering,
Tarbiat Modares University,
Tehran, Iran
**Tel:** +98-912-804-1675
**Email:** montazer@modares.ac.ir

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## Introduction

New e-learning solutions are intended to provide personalized and adaptive environments to address the learners' needs. Personalization of learning is in contradiction to the strategy of prescribing a single method for all learners. Today, learners are inclined to have their own learning experience in line with their personal needs, learning speed, interests, and particularly their own learning approach. They desire to peruse knowledge on their own terms and in their own preferred methods (1). In a personalized e-learning environment, the learning content is designed in consistence with the learner's individual requirements and learning style (2). Exploring learners' individual characteristics in the learning process can positively affect the their performance and increase their understanding and learning ability (3).

Improvement through personalized environments is a generally recognized practice (4). One of the personalized learning subcategories is adaptive learning. In addition to customizing the educational path based on individual characteristics (5), adaptive learning systems utilize the learners' data throughout a course in order to adjust the educational path and content of education in accordance with the complexity of educational resources and even the knowledge transfer methods (6).

Personalized learning systems are comprised of three major components: the "learner's model," "learning domain," and "educational model," or "adaptation engine" (7, 8). Each learner has different personal learning characteristics. In a personalized learning environment, learners' needs must be individually identified. This process is complicated and challenging given the individual characteristics of each learner (9). On the other hand, there are numerous personality traits that contribute to the learner's understanding and knowledge (10). To address this challenge in personalized learning systems, learners' prominent features are identified and modeled. Modeling is a quantitative representation of the learner using the Intelligent Educational System. In this regard, if the model is effectively designed, it can support the e-learning system to provide adaptive and personalized learning (11).

Each learning model combines various components of the learner's individual characteristics in different learning domains (12). The learning domains are the classifications of learners' individual characteristics based on the existing relationships among the elements of these characteristics, namely cognitive, non-cognitive, behavioral and emotional features, among others. The educational model is the strategy for the delivery of personal training in educational systems, which defines the required materials to adapt and the right adaptation time and procedure (8).

Based on the parameters in the learner model, an educational model is generated to personalize the interaction between the learner and the environment. In other words, to generate a learner model, one should identify and collect the learner's information. Furthermore, adaptive training can be delivered by means of updating and using the collected information (13, 14).

The present study provides a systematic literature review of the personal characteristics affecting personalization. Additionally, it aims to find the most commonly used methods for identifying the features contributing to a new learning classification, which have not been thoroughly studied to date.

## Methods

This was a systematic literature review investigating the learner characteristics for a student model in e-learning environments. This review was conducted through a comprehensive investigation of various electronic databases, using selected keywords related to the fundamental research objectives.

This research method includes three primary stages. The first stage concerns defining the research objective. The second stage is a systematic literature review conducted by searching for and selecting the relevant studies and articles. The final stage entails combining and analyzing the data extracted from the selected papers. The results of this analysis are presented in the following section, which concentrates on providing the conclusion, controlling quality, and the study's findings.

### *Aims*

In this research, identifying the goals related to the literature review of learners' characteristics in personalized e-learning environments is first performed by recognition of those characteristics. This study pursues three primary objectives:

1- Identifying the most commonly noted learner characteristics in learner modeling process

2- Implementing an appropriate domain categorization of these characteristics

3- Identifying the method of utilizing these characteristics in learner modeling process in various studies.

### *Search Strategies*

Initially, a few basic examinations were carried out to identify and select general and significant information regarding the related keywords and criteria. The utilized search string was as follows: ("Personalized" OR "Personalization" OR "Adaptive" OR "Adaptable") AND ("learning" OR "e-learning" OR "instructions" OR "education" OR "tutoring" OR "Intelligence tutoring system (ITS)" OR "Learning management system (LMS)").

Additionally, another search string was used for each domain to search for relevant

**Table 1.** The keywords searched in the proposed domain and individual characteristics of each of them

| Domain | Individual Characteristic | Keywords in search | Researchers Studied |
|---|---|---|---|
| Cognitive | Learning style | ("User model" OR "Student model" OR "Learner model" OR "Educational model") AND ("Cognitive" OR "Learning style" OR "Learning type" OR "Cognitive style" OR "Cognitive type" OR "Prior knowledge" OR "Background knowledge" or "Capacity and working memory" OR "Personality" OR "Age" OR "Gender" OR "Verbal ability" OR "Writing ability" OR "Spatial ability") | (15-19) |
| | Cognitive style | | (9, 20-23) |
| | Capacity and working memory | | (24-62) |
| | Personality | | (21, 27-30) |
| | Prior or background knowledge | | (31-34) |
| | Age | | (35-37) |
| | Gender | | (38, 39) |
| | Verbal, writing, and spatial ability | | (40, 41) |
| Metacognitive | self-care, self-assessment, self-regulation, self-awareness, self-explanation, self-monitoring, self-learning and self-management | ("User model" OR "Student model" OR "Learner model" OR "Educational model") AND ("Metacognitive") | (42-45) |
| Emotional | Positive and negative emotions | ("User model" OR "Student model" OR "Learner model" OR "Educational model") AND ("Positive and Negative Emotion" OR "Psychomotor" OR "Affective") | (46-50) |
| Behavioral | Learner's different behaviors during learning | ("User model" OR "Student model" OR "Learner model" OR "Educational model") AND ("Behavioural") | (51-53) |
| Motivational | Motivation | ("User model" OR "Student model" OR "Learner model" OR "Educational model") AND ("Motivational" OR "Motivation" OR "Expectations" OR "Goals" OR "Self-efficacy" OR "learning preferences") | (54-58) |
| | Goals | | (59-61) |
| | Self-efficacy | | (62-65) |
| | Expectations | | (66) |
| | Preferences | | (67-69) |

articles in that domain based on learner characteristics. These keywords are presented in Table 1. For instance, for the cognitive domain, the used search string was: ("User model" OR "Student model" OR "Learner model" OR "Educational model") AND ("Cognitive" OR "Learning style" OR "Learning type" OR "Cognitive style" OR "Cognitive type" OR "Prior knowledge" OR "Background knowledge" or "Capacity and working memory" OR "Personality" OR "Age" OR "Gender" OR "Verbal ability" OR "Writing ability" OR "Spatial ability") .

### *Inclusion Criteria*

This study attempts to investigate student characteristics in a learner model. In this regard, the studies that cover each characteristic in a learner's personality are included. Therefore, the following specifications are considered in the selection process. The studies are written in English and Persian language. Their full texts can be accessed, have addressed components of learner model and have been published in journals, conferences, technical reports, and books of academic databases.

### *Selection Process*

The above mentioned keywords were searched in different online databases to find relevant publications. Different academic databases such as IEEE, Science Direct, Springer, and Wiley were explored for that purpose. Using this method, 243 articles were selected.

Some specific criteria were considered for selecting the related articles in the screening process. Moreover, the research articles that focus on students' characteristics as variables of personalized e-learning environment design in learner modeling were included.

In this stage, 132 articles were excluded due to irrelevance to student modeling in designing a personalized or adaptive e-learning environment.

Ultimately, based on the designated criteria, the related articles were selected from those published in English and accessible in full text. Among them, 56 articles were chosen for qualitative synthesis. The other 55 were excluded due to analyzing the student criteria similar to the selected articles of their research (Figure 1).

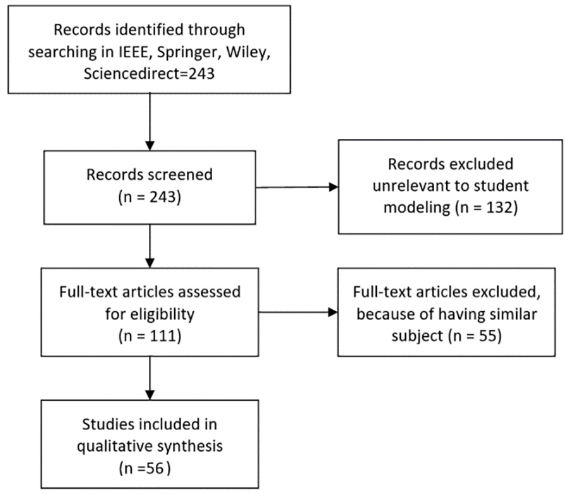


**Figure 1.** The diagram of research stages

### *Data Extraction*

All related articles with selected keywords were evaluated based on the selected criteria, and appropriate related articles have been selected. The collected studies were used to extract different characteristics for the learner's model. The extracted characteristics were categorized in various personality domains according to the proposed classification method of this study.

In each domain, each article's main idea and the proposed method are summarized and investigated to obtain the most important characteristic for the learner's model. Furthermore, the proposed method of each study for extracting these characteristics was also considered.

As a result of the database search, 111 reference studies were utilized. These publications were classified based on these categories: personality domain of used characteristic in modeling learner, utilized characteristic, publication date, and author(s). Table 1 represents all the reference studies that have been summarized in the present paper.

The numbers of summarized papers in each characteristic are demonstrated in

Figure 2.

## Results

Humans have individual and different characteristics. These differences are observed in a person's interaction with his/her surroundings in different aspects. In the case of investigating the individual differences in educational areas, not only do these characteristics not diminish but also new classes of characteristics that are associated with the learning process emerge, such as learning styles, cognitive styles, and metacognitive abilities (10).

Several characteristics about learning features have been investigated in previous studies (8, 10, 14, 21, 71-114). These characteristics have been used to design a personalized learning environment and be categorized into six different primary categories.

The proposed categorization for the learning domain includes five primary categories of "Cognitive characteristics," "Motivational characteristics," "Behavioral characteristics," "Emotional characteristics," and "Metacognitive characteristics." Moreover, there are also several characteristics resulting from combinations that are called "Combined characteristics." Each learner has a set of these features.

A. Cognitive characteristics refer to brain-based processes. These are the processes that control and regulate our behaviors and include characteristics like learning style, cognitive style, prior or background knowledge, capacity and working memory, personality, age, gender, verbal ability, writing ability, and spatial ability.

B. Metacognitive characteristics could be summarized as knowledge of knowledge itself. In other words, the ability to know and regulate an individual's thinking process and the encompassments of conscious control of cognitive processes such as memory, attention, and understanding. It includes self-care, self-assessment, self-regulation, self-awareness, self-explanation, self-monitoring, self-learning, and self-management.

C. Emotional characteristics correspond to an individual's emotions. They include positive emotions such as excitement, engagement, pleasure, challenge, hope, satisfaction, relief, pride, negative emotions such as disappointment, fatigue, confusion, shame, despair, anxiety and anger, and the victory of the lesson's discoveries.

D. Behavioral characteristics are based on

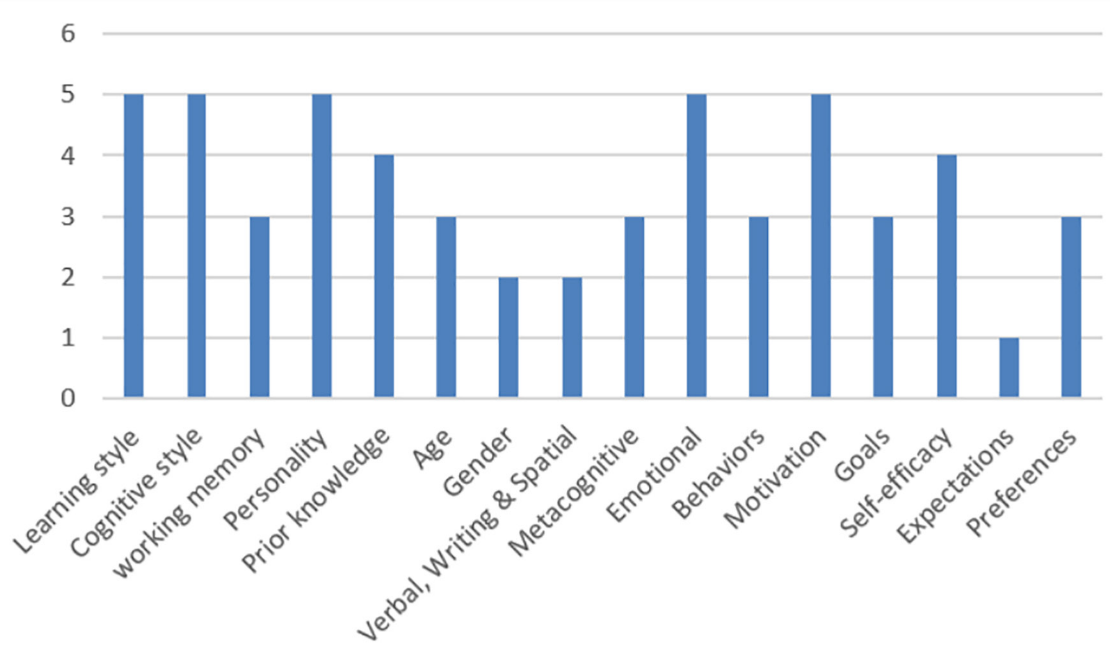


**Figure 2.** Number of summarized papers concerning each characteristic

the behavior of an individual. These include learner behaviors during the learning process, such as spending time on learning, quizzes scores or proactive behavior, incompatibility, learner control, requiring help and feedback, work effort (such as practice and scores), focus, ability to function in crisis, stress and other similar characteristics.

E. Motivational characteristics are related to one's motivation. This notion involves the process that initiates, guides, and continues toward goal-oriented behaviors. It causes an individual to act and includes motivation, expectations, goals, self-efficacy, and learning preferences.

F. Combined characteristics also include a combination of characteristics involving more than two learning categories.

In the following, each of the characteristics categories and their inter-relations is introduced (Figure 3).

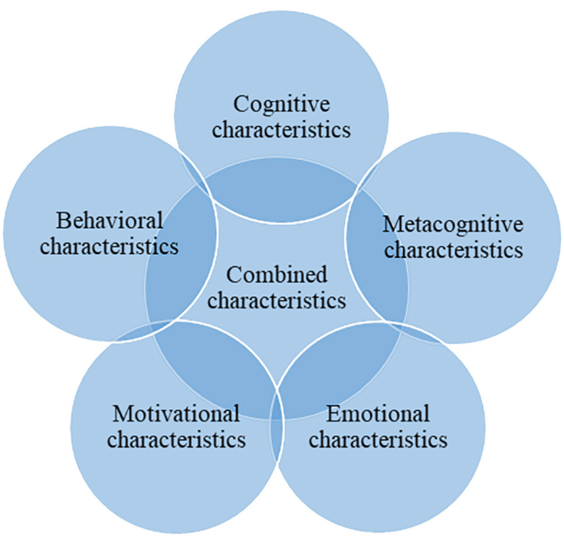


**Figure 3.** Suggested learning domains

## *Cognitive Domain*

This category includes characteristics related to the learner's established profile, such as learning style, cognitive style, prior or background knowledge, capacity and working memory, personality, age, gender, verbal ability, writing ability, and spatial ability. They are usually cannot be observed directly; moreover, they cannot be conveniently measured. However, they positively contribute to system performance improvement. Another feature of these characteristics is their relative stability during the learning process. According to references (10) and (70), cognitive characteristics are most popular in personalized e-learning systems. In the following, each of the cognitive category characteristics is briefly described, and the corresponding researches are provided.

### *Learning Style*

One of the most important learning cognitive characteristics is learning style. This characteristic is the most popular individual learning feature for personalized learning researchers (1, 10, 70, 74). Learning style is not represented by a precise and specific definition; nevertheless, it refers to some kind of learner-specific personality, such as the power, willingness, and ability to process information in learning (74), and in the preferred approach for learners to learn. Researchers define learning styles as: "to describe attitudes and behaviors that determine the preferred method of learning individually." For example, some learners prefer to learn by a picture. In contrast, text-study learners may learn by reading a text. Some learners choose to start collaborative learning with colleagues rather than learning individually (1).

The three most famous identification theories for the learning style are Felder & Silverman (75), Honey & Mumford's (76), and Kolb (77), each of which describes and identifies the learning style of the learner. Most researchers have applied the Feld-Silverman model to identify learning styles (1, 74, 78-80). After the Folder and Silverman model, Honey and Mumford, and Kleeb's model are most considered in papers. Other methods for identifying learning styles such as Wark and other techniques have been less regarded by researchers of this field (1).

Traditionally, learning styles are measured using surveys and questionnaires that can be long and tedious for the corresponding audience; moreover, the updating process would be burdensome in these cases. On the other hand, e-learning systems enable researchers to diagnose and analyze learner's learning styles through their online behaviors by examining the audiences' operational data (81, 82). Some researchers exploit an online forum, the spent time on quizzes, performance in quizzes, number of false questions or number of interactions, raised questions, the attendance duration in the system, and the number of requested guidance as indicators for identifying learning styles (15). Chen (83) presented an enhanced recommendation method named Adaptive Recommendation based on Online Learning Style (AROLS), which implements learning resource adaptation by Algorithms of mining learners' behavioral data that are used to identify learning styles from learner behavior include Bayesian networks (82), artificial neural networks (84), Decision tree (85), rules-based methods (86). In the studies (1) and (74), it has been stated that most of the identified methods among the intelligent techniques of learning algorithms are based on rules.

### *Cognitive Style*

The cognitive style includes the established features of individuals regarding obtaining, processing, and organizing information. It is commonly recognized as the learner's thinking style. Cognitive style is an individual's common approach to solving a problem, which includes the way of thinking, attitude, and comprehension of the learner, and the main building blocks related to general patterns of information processing (10, 87). After the learning style, the cognitive style is the second most interesting characteristic of the individuals in the education personalization field (70). Some of the most well-known learner's cognitive styles are "field independent" or "field-dependent" (88, 89), "analytical" or "global" (90) and "verbal" or "Imagery" (91). In general, independent field learners are "analytical", and dependent field learners are "global" (92). Learning differences in cognitive styles lead to different strategies of educational methods presentations. In many studies, cognitive style is selected as one of the most influential variables in the design of intelligent tutoring and adaptive systems (9, 20-23).

### *Capacity and Working Memory*

A certain amount of information that the learner can obtain, process, maintain, and retrieve depends on the amount of working memory, prompt learning ability, and understanding the concepts, logical thinking, and reasoning of the learner's IQ. Working memory plays a significant role in supporting learning since learners must store information in their minds during the learning process. Lusk describes the working memory as an individual characteristic that includes the simultaneous processing of a task, storing the related information in memory, and retrieving information from long-term memory (93). In some studies (24-26), the effect of working memory capacity and learner IQ on personalized and comparative learning have been examined.

### *Personality*

The human personality is a set of logical attributes such as the way of thinking, feeling, and excitement. Philip and Gerald define personality as characteristics of behavior, cognition, and emotional patterns; moreover, they recognize it as one of the environmental and biological factors (94). Generally, personality traits are stable and described as individual differences in behavioral, cognitive, and emotional patterns. Environmental, biological, and individual changes and interactions between individuals cause personality traits' stability in adulthood; thus, these characteristics can rarely change (95). This feature affects a learner's choosing method in selecting the content of preferential learning and learning approaches such as information gathering and communication with others. Additionally, it affects study behavior and learner's activity and performance (96). In this context, there are two known models for understanding personality. Five-factor model (97) and Myers-Briggs Type Indicator model (MBTI) (98). These two models can cover the behavioral characteristics of the learner's personality and are recommended for utilization in network learning (99). In the five-factor model, individual personality differences are determined in five dimensions:

1. Neuroticism
2. Extraversion
3. Openness
4. Agreeableness
5. Conscientiousness (100).

In the MBTI model, individuals have four personality dimensions:

1. Extraversion / Introversion
2. Sensing / Intuition
3. Thinking / Feeling
4. Judging / Perceiving.

Traditionally, the learner's personality was explicitly extracted through a questionnaire. In some researches, analysis of learner's network behavior has been regarded to extract the learner's personality (21, 28). According to reference (70), Personality traits are the third most important characteristic in e-learning researches (70).

### *Prior Knowledge*

Another characteristic of the individual learner is prior knowledge. If the learner understands a particular subject, he also perceives the prerequisite; conversely, the weakness in learning a subject indicates a learning weakness in its prerequisite (71). In evaluating quizzes, solving lesson exercises, predicting the problem-solving method, understanding a subject's importance, and the superior and more prompt learning indicate the learner's greater prior knowledge.

### *Age*

Learner age can directly influence other learner characteristics such as motivation, IQ ability, verbal abilities, writing ability, spatial mapping, emotional, behavioral, or motivational features. According to Nakic and Granic, learners' age effects are usually concerned with their previous experience and knowledge (10). Kabassi and Virvou have also considered an adaptive tutoring approach based on the level of knowledge, age, habits, and problems for adult learners (101). In a study by Kallinen and Ravaja, various parameters have been investigated, including age, gender, level of education, level of computer user experience on the evaluation of understanding, importance, passion, and interest in the news. Moreover, the brain and facial muscles' activity through specific electrodes have been examined (36).

### *Gender*

It cannot be stated that a particular gender is superior in terms of learning. The brain structure of some people, apart from their gender, is more effective. Genetic, environmental, and cultural differences, developmental and structural differences, differences in learning styles, and different hormones of men and women indicate the impact of gender in learning that can be important in designing e-learning systems. Some researchers, such as Munoz-Organero, do not consider gender an effective parameter in the learning process (102). In the research of Nakic and Granic, gender corresponds to learning behavior, motivation, and the result of learning (10). In a study by Shabani, which is conducted among 132 foreign language learners, different dimensions of learning styles based on the learners' genders are investigated. This study's results represent similarities and differences in the learning styles preferred by male and female participants (38). In another research by Noguti, gender differences of incentives have been investigated in using social networks. The research has presented that female users utilize social networks more than male users to search the corresponding information of studying and learning new contents and discuss the products (39).

### *Verbal, Writing, and Spatial Ability*

Other characteristics of the learner are verbal, writing, and spatial abilities. Verbal ability is the learner's talent in communicating with the teacher and other learners through talking. A person with superior verbal can ask questions from the instructor and solve his/her ambiguities more conveniently. In the research of Patterson et al., the verbal ability impression on learning has been studied. In this research, it has been demonstrated that learners with weak verbal ability are more comfortable in using a knowledge map than a text in learning. Knowledge maps have a more effective impact on text-based learning for learners with weak verbal ability (Patterson et al., 2003). Therefore, in e-learning systems, it is possible to assess the level of a learner's verbal ability through an adaptive way to increase learning efficiency. In a study by Nakic and Granic, the verbal ability was also considered as one of the learner's individual characteristics (10). However, this feature is less considered in other researches.

Writing talent is defined as the ability to write and take notes through the learning process. This ability can also be advantageous in learning and summarizing writing exercises and responding to quizzes. The writing ability in e-learning systems can be significantly useful in textual context environments due to limited required verbal communication in communicating with the instructor and other learners. In the research of Alepis & Virvou, it has been suggested that angry people have numerous mistakes in writing words, and people tend to express feelings when they feel negative (35). Writing ability is rarely regarded as an interesting parameter to be considered by scholars.

Spatial ability is considered the potential to draw and imagine three-dimensional spaces in the learning process and multimedia content. This ability dramatically contributes to learning, especially the fields that require spatial visualization, such as practical lessons. Learners with low spatial ability can be significantly supported by animation instead of non-visualization or using 3D images rather than using two-dimensional images in the learning process (103). Multimedia, animation, and three-dimensional images play a crucial role in spatial learning. The critical point to note is that this ability is considered more than writing and verbal ability by e-learning researchers. In the research of Xiao et al., an adaptive training system is presented for teaching visual-spatial skills (41). In another study, Van Nuland & Rogers reviewed spatial visualization's effect on learning medical lessons (40).

### *Metacognitive Domain*

Human contemplation regarding his/her mental processes and thinking about thinking is called metacognition. It includes knowledge of time and utilization procedure of specific strategies in learning or problem solving (104). Cognitive knowledge and cognitive regulation are two main meta-cognitive components. Metacognitive knowledge is the learner's information about him/her-self and the method that the individual gets to benefit from it. In a study by Flavell, metacognitive knowledge was considered as the storehouse of personal knowledge of self-knowledge, tasks, goals, activities, and experiences. It was divided into person knowledge, task knowledge, and condition knowledge (105). Hadwin defines metacognitive knowledge as something that the learner knows and believes in him/her-self. His/her describing method of the task and his/her strategy in completing a work (106).

The metacognitive regulation consists of the learner's individual method and the learner's utilization method of metacognitive knowledge to change mental processes and arrange them to control learning (107). Metacognitive regulation includes planning, monitoring, and evaluation (108). One of the most efficient approaches for improving e-learning is enhancing the learner's individual metacognitive characteristics. These features include individual self-care, self-assessment, self-regulation, self-awareness, self-explanation, self-monitoring, self-learning, and self-management.

### *Emotional Domain*

The emotional characteristics are described as the changes in the learner's interest, feelings, morale, and attitudes during the learning process. These characteristics can be controlled and appropriately trained through five stages of receiving, responding, valuing, organization, and internalizing (109). Psychological researches have illustrated that positive emotions are associated with increased creativity, cognitive flexibility, efficiency and professional satisfaction, access to communication skills, and negotiation. Feeling disorganization, ineffectiveness, and self-defense may also activate negative feelings such as avoidance, retreat, denial, and aggression (110). Thus, emotions directly affect learning performance (50). Therefore, the purpose of the emotional state measurement is to control the emotional state of the learner. In traditional classes, this is one of the teacher's responsibilities. In the e-learning environment, the intelligent tutoring system engine is responsible for identifying and controlling the learners' emotions.

For instance, the system can display a decent message and create modifications in the training process by identifying a learner's fatigue sensation. In a conducted study by Woolf et al., Hardware and software methods have been utilized to identify learners' emotions (46). In another study by D'Mello et al., learner's fatigue measure has been identified using eye movements (47). In Fatahi's research, the learner is modeled based on the individual characteristics of personality and emotion (48). Another research has been proposed to persuade the learner to continue listening by using learner's affective behavior (49). In Chen and Sun's study, various multimedia impressions on the learner's emotions and visual and verbal performance have been investigated (50).

### *Behavioral Domain*

The learning process is related to human behavior type. The so-called "learning theory" is often associated with a behavioral perspective. The behavioral approach focuses on identifying the impression of the environment on the learner's apparent behavior. In this view, it is assumed that the mind is a black box that cannot be observed. The only approach for understanding an individual's mind procedures is through observing his/her apparent behavior (111). Face-to-face communication between learner and instructor enables the instructor to identify the learner's problems and improve the learning process through corrections (112). Instead, in e-learning systems, a learner's behavior can be identified from his/her network behaviors, interaction with the system and other users, or questionnaires. These can be used to personalize the system. The learner's behavior can be exploited in three steps of "collecting and recording interactions," "selection of attributes," and "analysis." "Collecting and recording interactions" includes collecting learner interactions with the system, which can be stored for later processing. "Selection of attributes" involves selecting a part of the training system design that provides useful information about the learner. In the "analysis" phase, the collected information is processed and compared with the previously described behavioral patterns. Moreover, it adapts the system to the learner's characteristics (21). The behavioral characteristics in e-learning systems are considered influential variables in other user attributes.

### *Motivational Domain*

Learning efficiency is a critical factor that can be influenced by the learner's motivational characteristics, along with the instructional methods. The motivational feature aims to provide learning opportunities by creating passion, excitement, and learning motivation in learners. Learner's engagement characteristics include motivation, expectations, goals, self-efficacy, and learner's learning preferences. In the following, each of these characteristics is explained.

### *Motivation*

Motivation can be defined as a measure of continuous efforts toward achieving a goal. In other words, learning motivation is the amount of continuous effort that the learner makes toward learning (58). Motivational learning is a prerequisite for deep processing of learning content and stable maintenance functions. Furthermore, it is a foundation for the enjoyment of learning and durable interest (54). This feature is not an intrinsic and constant element. Thus, it may improve over time, especially in providing appropriate teaching strategies and learning environments for the learner (60). Motivation consists of two parts: intrinsic motivation and extrinsic motivation. It includes being curious, challenging, and willing during the learning process in people with intrinsic motivation. It includes acquiring a satisfactory score in people with extrinsic motivation, competing with others, and attempting to obtain a badge for the goal (21). Motivation is an influential factor in e-learning (113). The factors of "individual attitude and expectations," "transparent orientation," "recognition and reward," along with a comfortable learning environment, can increase the motivation for e-learning (58).

### *Goals*

The learner's goals include the intention and motivation toward learning. "Orientation" is the most common feature of learning goals. "The theory of goal orientation" discusses the impression of goals on learning performance. Orientation is defined as a set of intrinsic behaviors that determine learners' selected approaches and their learning encouragement method. The goal orientation can be described as a set of learners' beliefs that illustrate their goals and explains the significance of their goals.

The goal orientation includes learning goals and performance goals. The learning goals are the subjects that the learner seeks to master. The performance goals are the other individuals' perspectives regarding the learner's performance (21). The orientation of the learning and performance goals represents two different perceptions of success and denotes different goals for participating in the learning process.

### *Self-efficacy*

Bandura defines self-efficacy as a deep belief in organization and implementation of necessary actions in the upcoming situations. In this regard, Bandura considers four primary sources for self-efficacy: mastery experiences, vicarious experiences, verbal persuasion, and physiological and affective reactions. According to Bandura, the most important method to gain a strong sense of self-efficiency is to see successful "mastery Experiences." By observing the "successful experiences of others" in fulfilling the tasks and efforts, one can gain belief in his/her ability to succeed. Through "verbal persuasion," the individual is convinced that he/she has the required skills and abilities to succeed.

Additionally, "physiological and affective reactions" in various situations can affect the person's sense of efficiency in a particular situation. People with high self-efficacy see the problems and challenging issues as a procedure for gaining skills. These people have a passion for activities participation and represent an outstanding commitment and responsibility. Failures will not be a hindrance to them. In contrast, individuals with low self-efficacy avoid challenging tasks and consider the accomplishment of arduous tasks beyond their abilities. They are severely affected by their failures and suffer from a lack of self-confidence.

Self-efficacy significantly contributes to the learner's motivation and the effectiveness of learning. Furthermore, it increases the learner's self-esteem and plays a significant role in achieving learning goals. In online learning environments, the learner's sense of efficiency and success can be provoked. His/her self-esteem can be increased by providing straightforward initial content to determine the learner's ability and then complicate it.

### *Expectations*

The expectation is defined as a momentary belief in the probability of realizing a particular action that results in a particular outcome. It must be considered that the expectation attribute consists of the prediction and the probability of performing a behavior. Simultaneously, the self-efficacy feature is the individual's confidence in a behavior conduction's ability (114). Additionally, effective expectations aid the learner in trusting his/her abilities and performing accordingly to achieve the desired results. The learner's expectations are consistently influenced by the individual's attitude toward e-learning and make a long impression on the learning process (66).

### *Learning Preferences*

One of the characteristics that have been investigated to a lesser extent by the researchers is learner preferences. Learning preferences mean considering the learner's opinion and attitude in the learning process to enhance and facilitate the quality of teaching services. The learning process's quality is not supposed to be delivered by the instructor to the learner; however, it is the process of collaboration between the learner and the learning environment. This means that the "product/result of the learning process" is not merely a result of the production process at the educational institution; nevertheless, it also relies on the empowerment and activation of the learner (67). In e-learning systems, the learners' preferences in cookies or databases, can be stored and used by considering their previous opinions and beliefs, along with using their network behaviors.

## Discussion

Different categorizations of student modeling have been previously presented; however, a comprehensive model that considers a wide range of learner's characteristics in the personalization of the learning environment has never been realized in the previous studies.

One of the most utilized categorizations is bloom categorization, which has classified learner characteristics into three main categories, including "Cognition," "Affective," and "Psychomotor" (115). As the first learning category, cognitive is an information processing pattern that uses logical thinking to create and acquire a knowledge base during the learning process (70). This category's characteristics are usually stable and unchangeable. The required duration for changing them in individuals occurs in an extended period (21). Researchers believe that this category consists of learning style, cognitive style, prior knowledge, capacity, working memory, thinking process, learning goals, and goal orientation (8, 14, 21). The second category includes the learner's emotional or affective characteristics that can be regarded as a positive or negative emotional attitude. Positive emotions encompass excitement, interaction, pleasure, challenge, hope, satisfaction, relief, pride, and negative feelings, including despair, fatigue, confusion, shame, despair, anxiety, and anger.

Moreover, self-efficacy and the victory of explorations typically fall into the emotional category (8, 14, 70). The third category is the behavioral or psychomotor characteristics describing various styles of learner behaviors and correspond to the learner's cognitive or emotional states. The behavioral characteristics include preventive behaviors, inconsistency, comprehensive control, seeking help and feedback, attempting to perform activities (such as exercises and scores), concentration, learning ability, and cognitive ability (8, 70).

In a research conducted by Normandy et al., the combined category has been added to the Bloom category. This research suggests that in some research in this field, several individual characteristics are used in different categories to increase the reliability and performance of the adaptive learning environment for assisting the learner. Therefore, combined categories can be added to the Bloom category by combining characteristics from cognitive, emotional, and behavioral categories. In this research, some of the influential characteristics, such as verbal, writing, spatial abilities, goal orientation, and self-efficacy, are not considered (70).

In another study by Brusilovsky and Milan, approaches and learning modeling techniques in adaptive learning systems have been investigated. In this research, individual characteristics including user knowledge, interests, goals and tasks, background and personal characteristics of cognitive styles and individual learning styles are considered, and cognitive and personality abilities are briefly illustrated. Other personal characteristics in learning environments, such as motivation, metacognitive abilities, and emotional factors that play an essential role in learner modeling, are not regarded (71).

In Thalmann' study, 30 adaptive learning systems have been analyzed. The importance degree of user attributes impacts and system characteristics have been examined with 13 various criteria including knowledge structure, user history, user requests, prior knowledge, knowledge domain, presentation preferences, preferences for media types, learning style, language, device requirements, bandwidth, location, and user status. In this study, the abilities and cognitive style of learners are not considered (72).

In Grimley and Riding's study, personal characteristics of cognitive style, gender, working memory, knowledge, and anxiety are considered highly effective in adaptive learning systems. Generally, the potential interaction between the variables in learning performance is discussed in case variables are essential. Moreover, their role during the learning process has been examined (73).

In a conducted research by Chrysafiadi and Virvou, the level of knowledge, skills, learning preferences and learning styles, mistakes, and misconceptions, motivation, emotional characteristics, cognitive aspects such as memory, attention, problem-solving, decision making, experience, analysis, critical thinking and communication skills and metacognitive aspects such as self-regulation, self-explanation, self-evaluation, and self-management are regarded as individual characteristics (14).

Nakic et al. introduced 22 individual learner characteristics by evaluating 98 articles; however, no precise categorization of individual learner characteristics has been presented in this study. These characteristics include age, gender, perceptual speed, processing speed, capacity and working memory, reasoning ability, verbal ability, spatial ability, cognitive ability, metacognitive ability, psychological skills, personality, anxiety, emotions, cognitive style, learning style, experience, background knowledge, motivation, expectations, preference, and interactions (10).

In a conducted research by Ghorbani and Montazer, different categories for the learner characteristics have been presented, which includes three categories of "cognitive," "motivational," and "emotional." In this study, it has been pointed out that each learner has a set of these characteristics. Cognitive features include individual characteristics of learning style, cognitive style, memory, IQ, and personality. The category of motivational features encompasses individual motivational characteristics, goal orientation, self-efficacy, and knowledge. Finally, the category of emotional features includes the learner's emotional states, such as failure, confusion, happiness, and assurance. In this research, the behavioral and metacognitive characteristics of users have not been regarded (21).

In this paper, all characteristics of learners that have been previously utilized in other studies for personalization of the system based on learners' attributes have been investigated. This study aims to present a comprehensive classification that considers the previous classifications and includes more characteristics and presents some categories that have not been regarded thus far. In this regard, a novel classification of learner characteristics was proposed considering 22 effective features. The proposed categorization for the learning domain consists of five primary categories of cognitive characteristics, motivational characteristics, behavioral characteristics, emotional characteristics, and metacognitive characteristics. Moreover, some other characteristics are shaped through a combination of other characteristics. A set of these features represents each learner. In this paper, each of the categories, along with the related characteristics, was introduced. The corresponding studies for each of the characteristics were examined. The research results can be considered a clear and accurate road map for future research on learner modeling in e-learning systems. Future studies can utilize this categorization to select influential characteristics in the personalized system design process through this aspect. For example, by choosing two different learners' traits like personality and motivation, it can be assumed that two different cognitive and metacognitive aspects are considered in student modeling.

To summarize, influential personal characteristics in the personalization process are considered in the present paper. The most common methods for identifying features in different learning domains were introduced. Moreover, a new categorization of learner characteristics based on the results has been provided for user modeling. The classification of students' traits can be beneficial for learning environment designers since they can choose the learner's most efficient characteristics to efficiently personalize the system .

This research's limitation includes limited access to the researchers that published their studies in languages other than English or Persian.

## Authors' Contribution

Study concept, design, and critical revision of the manuscript for important intellectual content were developed by the authors who participated in all the research process stages.

## Conflict of Interests

The authors declare that they have no conflict of interests.


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