Mastering Learning the Role of AI in Forestering

Dr. M. Revathi
Assistant Professor, Department of Commerce
Erode Arts and Science College Erode

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Abstract

Artificial Intelligence involves the development of machines with an adequate level of Intelligence capable of performing human-like functions such as cognition, decision-making, learning, and adapting to the environment. In recent times, Artificial Intelligence has been extensively applied in instruction and learning to improve learning outcomes. Learning in the classroom may only be effective or proficient for some students due to differences in personality, learning preferences Etc. This study aims to find an optimum basis to classify learners and suggest a conceptual model that leverages Artificial Intelligence to foster mastery learning for uniform and improved learning outcomes through the review of relevant literature.

Keywords: Artificial Intelligence, Mastery Learning, Education, Learning Preferences, Inclusive Learning.

Introduction

Artificial intelligence is a discipline and the following innovations and progress that have led to computers and machines acquiring the ability to perform human- like functions indicated by cognitive abilities such as intelligence and pattern recognition, learning, adaptability, Etc. Artificial intelligence has been extensively used in education (Chen et al., 2020). Similarly, According to McCarthy (2004), Artificial Intelligence is the science of instilling intelligence in machines or, more specifically, developing intelligent computer programs capable of simulating human intelligence.

Chen et al., (2020) found that AI and the usage of Machine Learning and adaptability have resulted in the customization of curriculum and content to provide personalized learning experiences per the learners' preferences, which has led to improved learning outcomes. Supporting the above finding, Holmes et al., (2020) imply that Artificial Intelligence in the education sector includes personalized instructional and dialogue systems, intelligent agents in game-based environments Etc. Similarly, Yufeia et al., (2020) indicated the application of AI in education to the usage of data mining and intelligent analysis of educational data, learning analysis Etc. to provide customized learning experiences.

Keefe (1979) described learning styles as the sum of cognitive, affective, and physiological factors influencing how individuals perceive, learn and respond in a learning environment. While Keefe (1979) emphasized the factors that influence perception and learning, (Stewart & Felicetti, 1992) focused on the learner's preferences. Hung (2012) suggests that

complementing teaching techniques to students' learning styles is critical to improving learner effectiveness. Bloom (1968) opined that most students could master the content or the subject taught to them. Mastery learning pertains to a teaching strategy that suggests that all students must achieve a basic level of mastery in a current topic before learning the following content or topics. The above discussion necessitates using Artificial Intelligence to provide customized learning experiences and foster mastery learning to achieve improved and uniform learning outcomes. Considering the above, this study aims to find a suitable basis for classifying learners to provide personalized learning experiences and to suggest a conceptual model that leverages Artificial Intelligence to foster personalized learning and mastery learning for achieving improved learning outcomes.

Review of Literature

Artificial Intelligence and Adaptive Learning

Artificial intelligence refers to the development of intelligent machines capable of simulating and performing human functions such as cognition, learning, decision- making, and adapting to the environment. Adaptive learning is an educational strategy that leverages computing algorithms to assemble the interactive learning experience and adapt to the learning preferences of individual students (Kolchenko, 2018). Similarly, Nguyen & Do (2008)opine that adaptive learning involves tailoring or customizing learning material, such as content, exercises, tests, Etc., according to the learners' preferences and characteristics.

Adaptive learning systems offer various benefits. Using learning analytics and real-time analysis has improved student achievement and knowledge retention. For example, Duolingo, an application used to learn spoken languages, increased learner autonomy by customizing time, finding materials, and modifying techniques to achieve better results (Alam, 2022). In support of the above finding, other studies Dhakshinamoorthy&Dhakshinamoorthy (2019)found that students who used a proposed adaptive learning methodology showed a performance improvement. (Sivakumar et al., 2015)opine that adaptive e-learning provides several benefits, such as increased knowledge retention, improved knowledge sharing, consistent delivery Etc. According to Abhirami & Devi (2022), Web-based learning promotes educational equity and independent learning. Despite offering several benefits, Adaptive learning systems face certain downsides. For instance, Kolchenko (2018)points out that for adaptive learning systems to be effective, They would need high-quality and meaningful data for algorithm training, failing which the Artificial Intelligence program may perform worse. He further states that adaptive learning systems cannot replace experienced faculty as they have a firm grip on the subject and pedagogy.

Mastery Learning

According to Bloom (1968), Mastery learning is a philosophy or a teaching or learning strategy according to which students should only proceed to study advanced topics or concepts after achieving a certain level of mastery in the pre- requisite knowledge or the basic concepts. It is a philosophy that encourages inclusive learning. The principal focus of this strategy is ensuring that all students have mastered key or basic concepts before studying advanced concepts. Carroll (1963) opined that scholastic aptitude is not the best predictor of academic performance. Instead, it predicts the time needed to learn a particular subject. Basis this, Bloom (1968) argued that most students could attain mastery in a subject provided that the time and instructional strategy were personalized according to the learners' characteristics. In other words, He indicated that scholastic aptitude is not indicative of academic performance.

Many studies have confirmed the benefits and usefulness of the mastery learning strategy. A meta-analysis study by Kulik et al., (1990) revealed that mastery learning programs positively affect the examination performance of school and college students. Similarly, Clark et al., (1983) found that students in an undergraduate program who practiced mastery learning strategy indicated higher levels of achievement. Similarly, (Hussain & Suleman, 2016) also found that mastery learning profoundly impacts student performance and knowledge retention.

Learning Styles and Learning Preferences

The term "learning styles" indicates that learners prefer different instructional strategies or ways of learning to learn content effectively (Pashler et al., 2008). The VARK model is one of the most accepted model of learning styles. It classifies learners into Auditory, Visual and Kinaesthetic learners and suggests that learners learn best according to a preferred sensory mode such as visual, hearing Etc.

Although the VARK framework is extensively used to describe learning styles, It has faced criticisms. Riener & Willingham (2010) have criticized the VARK learning styles with the argument that learners' preferences to learn content through a specific mode, i.e., Auditory, Visual, or Kinesthetic, does not have meaningful implications for their learning. In other words, They opine that the learning outcome remains the same irrespective of the preference for mode of learning. They imply that most of what we learn is stored in terms of meaning and not limited to a robust sensory mode. In support of the above argument, an experimental study on chess players' perception conducted by (Chase & Simon, 1973) revealed that what we learn is stored in terms of meaning and that we are better able to learn and recall something if the content is more meaningful to us.

Considering the benefits of mastery learning, combining it with Artificial Intelligence to provide customized learning experiences to learners based on their personality and preferences is likely to improve inclusiveness and academic performance.

A Conceptual model of using Artificial Intelligence to foster mastery learning. Basis the above discussion, the proposed system or conceptual model will include elements from the following theories:

Carl Jung's Theory of personality

Carl Jung, A Swiss Psychiatrist, was one of the first to describe the personalities of introvert and extrovert. According to him, Introverts and extroverts have the following characteristics.

Introverts: Persons with an introverted personality may focus on their inner world and rely on reflection (Jung, 1923). According to Carrigan (1960), Introverts are individuals who get energy by being in solitude and often appear shy from social activities. Introverts are not outgoing and may prefer less stimulating or social activities. They prefer to be independent, learn through reflection, spend time alone, and be self-directed.

Extroverts: Jung (1923) characterized extroverts as individuals who prefer to interact with the external world. According to (Carrigan, 1960), Extroverts are individuals who get energy from being around and interacting with others. In other words, Extroverted Individuals derive energy from stimulation. Extroverts are outgoing and may enjoy teamwork or group assignments.

Preferred forms of assignments based on the discussion of Carl Jung's theory of personality and Kolb's learning styles. (McLeod, 2017)

Table 1 Classification of Learners based on Personality and Learning Preferences

Personality of the learner	Preferred learning style	Learning preference	Preferred assignments
	Converging	They prefer to experiment with new ideas and are practical. ituse knowledge to find solutions to problems or issues.	Assignments that will help the learner to gain critical thinking skills or the ability to think clearly, such as analysis of case lets, scenario analysis in the written form.
	Assimilating	They understand content by arranging them in a logical sequence and rely on logical theories.	Assignments that will help the learner to conceptualize and reflect through observation such as watching videos of lectures, reading journals, identifying patterns or analogies Etc.
Extroverted	Diverging	They prefer assignments or tasks which involve application of creativity and that require out-of- the-box-thinking.	Activities that facilitate out-of-the-box thinking such as brain storming, Rapid ideation Etc.
	Accommodating	They tend to rely on intuition rather than on logic and prefer an experiential approach to learning.	Case studies, Group projects, group discussion Etc.

As discussed in Table 1 above, Introverted learners are further classified into learners preferring a convergent learning style or an assimilative learning style. And extroverted learners are further classified into learners preferring divergent or accommodative learning styles and the preferred after class activities are mentioned for each of the combination.

A Four-Stage Model for Leveraging Artificial Intelligence to Foster Mastery learning

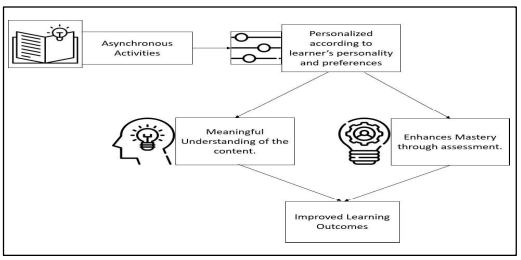

Figure 1 This Figure Illustrates a Four-Stage Model for using Artificial Intelligence to Foster Mastery learning

Stage 1 - Determination of learner's personality: The system detects the learner's personality through a questionnaire or data mining. Data mining in the education field refers to using student data such as Age, teacher feedback and grades, Etc., to determine the students' characteristics. Once the student's personality and learning style has been identified, We proceed to Stage 2.

Stage 2 - Assignment of asynchronous activities: At this stage, the learning preferences of the students have been understood. After completing one unit in class, the system automatically assigns asynchronous activities from an assignment bank or a database designed by the instructors to the learners according to their learning preferences as determined in Stage 1. The learner's personality and learning style is ascertained as discussed in Table 1. Furthermore, a fixed time is assigned to complete and submit the assignment, preferably before proceeding to the subsequent unit in class. Using Supervised machine learning at this stage is essential for automatically assigning activities based on learner characteristics. For example, Labelled data could be used to train algorithms that would be used to classify data which in turn would facilitate the automatic assignment of activities based on learner characteristics.

Stage 3 - Assessment: Assessment is done to check if the student has attained the basic or pre-determined level of mastery through a quiz or a suitable assessment method.

Stage 4 - Remediation: If the student has failed to achieve the basic level of mastery, The student is subject to remediation by providing additional resources such as materials, lectures, support Etc.,. The learner goes through the cyclical learning and assessment process until the desired mastery level has been obtained.

Discussion

Recognizing the need for personalizing learning experiences according to the learner's preferences to improve learning outcomes, The author suggests adopting the proposed model as an add-in to the existing Learning Management Systems of educational institutions to enhance students' learning outcomes.

As indicated by Simon and Chase, the content learned by learners is stored in terms of meaning. Therefore, It is critical to ensure that the instructional strategy has to be customized according to the learning preferences of the learners to make the content more meaningful to the learners to enhance learning outcomes. Considering the above argument, The proposed model suggests that learning does not occur uniformly in the classroom for several reasons. Therefore, The use of after-class hours by providing asynchronous assignments according to the learner's preferences may enhance a meaningful understanding of the content.

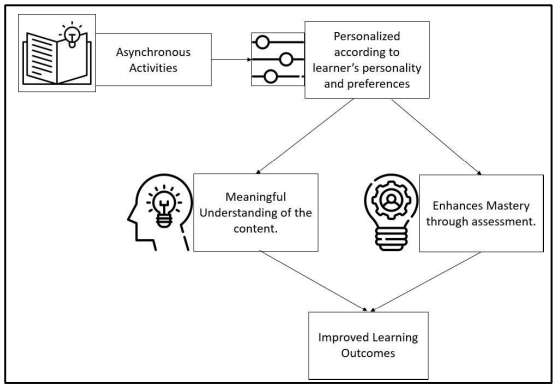

Figure 2 This Figure Illustrates the Conceptualization of the Proposed Model for Improved Learning Outcomes

Therefore, As illustrated in Figure 2 above, we conceptualize the idea of the proposed model as above. Asynchronous assignments or activities, when personalized according to the learner's personality and preferences, enhance the learners' meaningful understanding of the content and fosters mastery through assessment, which would result in improved learning outcomes.

However, Considering the challenges, Integration of the proposed model as an add-on to the existing LMS and it's effective use requires teachers to be trained on Artificial Intelligence and Machine Learning for successful implementation of the model.

Conclusion and Scope for Further Research

Personalizing instructional strategy according to the learner's personality and preferences is critical to enhancing a meaningful understanding of the content and facilitating mastery learning for improved learning outcomes. The proposed conceptual model in this study suggests the use of machine learning and artificial intelligence to use after-class hours to enhance mastery learning through personalized synchronous activities. Future work or studies can focus on the practical application of the proposed model, replication, and implementation of similar models in schools and colleges in rural areas to facilitate inclusive learning. Furthermore, Future research can focus on developing practical asynchronous activities to foster critical thinking and creative thinking skills that are much needed in today's world.

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