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A Study of Multimodal Intelligent Adaptive Learning System and Its Pattern of Promoting Learners' Online Learning Engagement

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As the field of artificial intelligence continues to evolve, so too does the application of multimodal learning analysis and intelligent adaptive learning systems. This trend has the potential to promote the equalization of educational resources, the intellectualization of educational methods, and the modernization of educational reform, among other benefits. This study proposes a construction framework for an intelligent adaptive learning system that is supported by multimodal data. It provides a detailed explanation of the system's working principles and patterns, which aim to enhance learners' online engagement in behavior, emotion, and cognition. The study seeks to address the issue of intelligent adaptive learning systems diagnosing learners' learning behavior based solely on learning achievement, to improve learners' online engagement, enable them to master more required knowledge, and ultimately achieve better learning outcomes.

Keywords: multimodal, intelligent adaptive learning system, online learning engagement

Introduction

The advancements in emerging information technology and intelligent systems are instigating a transformation in the field of education. For example, in China, the "Education Informatization 2.0 Action Plan" advocates the creation of a digital, grid-based, personalized, and lifelong education system that relies on various smart devices and networks. The plan also prioritizes the promotion of novel educational models and ecologies that leverage cutting-edge technologies such as artificial intelligence, big data, and the Internet of Things. While researchers have enhanced in online learning engagement and methodologies (Henrie, Halverson, & Graham, 2015), there is still a lack of research on multimodal learning analysis and implementation of intelligent adaptive learning systems with learning engagement, especially those supported by multimodal data.

To move from unimodal to multimodal data analysis, we need to augment data volume and use objective data to comprehensively and scientifically characterize embedded phenomena. Upgrading from an adaptive learning system to an intelligent learning system requires a shift from traditional data-based learning to

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personalized teaching based on learners' unique differences to achieve a "learner-centered" education. In this regard, Mou (2020) proposes a model for the multimodal intelligent adaptive learning system (MIALS) that enhance learners' online learning engagement, including their behavioral, emotional, cognitive, and social engagement, promoting meaningful learning and improving academic achievement.

Overall, integrating cutting-edge technologies and pedagogical approaches into education is crucial to provide learners with effective and personalized learning experiences. Therefore, researchers should continue exploring ways to develop and implement MIALS to enhance the quality of education.

Literature Review

Multimodal Learning Analytics (MLA) is a new field that optimizes the learning experience by analyzing learning behaviors within multifaceted environments through multimodal data. MLA emerged from the intersection of multimodal education, multimodal data, and computer-supported analysis (Mou, 2020). Blikstein and Worsley (2016) categorized MLA into nine fields, including text, discourse, note-taking, sketch, and action and gesture analysis. Studies have shown that MLA can evaluate and provide feedback on students' learning processes, as exemplified in Annemaree, Thilakaratne, Vivian, and Falkner's (2019) study, which offers targeted pedagogic interventions by understanding students' learning status. Similarly, Bahreini, Nadolski, and Westera's (2016) study demonstrates the efficacy of MLA in determining learners' emotional states through facial expressions, speech, and behavior signals, and in adjusting teaching strategies accordingly.

Intelligent Adaptive Learning System (IALS) is a self-adaptive learning system built on artificial intelligence technology that is more intelligent, precise, and reliable than traditional adaptive learning systems. The IALS takes education's "data-ism" to a more advanced stage of "intelligent-ism" (Zhou & Wen, 2020) and has found widespread application in education and teaching. Multiple methodologies for incorporating IALS in education and teaching have been explored. For instance, Yang, Gamble, Hung, and Lin (2014) show that IALS can effectively improve the English reading and writing abilities and critical thinking of online learning groups. Vanbecelaere et al. (2020) compared the effects of intelligent adaptive and non-intelligent adaptive electronic games on children's letter and language learning and found no significant difference in learning outcomes between the two conditions.

Learners' online learning engagement refers to maintaining a positive and fulfilling mental state in online learning, comprising three aspects: vigor, dedication, and absorption. Scholars have redefined learning engagement from three different facets: cognition, emotion, and behavior (Fredricks, Blumenfeld, & Paris, 2004). Scales are a commonly used method for detecting learners' online learning engagement. Nevertheless, measuring learners' online learning engagement through algorithms has become a new area of investigation in recent years. For instance, Atapattu et al. (2019) measured learners' cognitive engagement by accumulating their posts and coding philosophical posts as document vectors. Similarly, Liu, Xing, Zeng, and Wu (2021) employed logistic regression, Naive Bayes, decision trees, random forest, and support vector machine algorithms to identify learners' emotions and forecast their learning performance. Some scholars use the Bidirectional Encoder Representation from Transformers (BERT) model to measure learners' online learning engagement. (Zou et al., 2021).

In summary, MLA and IALS are two emergent fields of learning analytics that leverage diverse data sources to enhance the learning experience. MLA employs multimodal data to examine learning behavior, while IALS employs artificial intelligence for adaptive learning and monitoring learners' online learning engagement. Research on online learning engagement, which describes a positive approach toward learning, centers on developing algorithms to measure and analyze it. However, research on developing the MIALS framework and scrutinizing its modes and principles to foster learners' online learning engagement remains unexplored. Therefore, this study proposes the MIALS framework and examines its principles and methods for improving learners' online learning engagement.

The Framework of MIALS

A MIALS is composed of three layers: the data layer, the logic layer, and the user layer. The data layer serves as the foundation of the system and includes learners' multimodal data, learning resources data, basic learner data, and learner learning process data. Learners' multimodal data encompasses affective, language, physiological, and neural data. Learning resource data includes various materials such as test papers, courseware, and online course data. Basic learner data contains enrollment information and operation logs, while learner learning process data capture learning behavior logs, textual data, and exam data. The logic layer is responsible for addressing learners' engagement in online learning through algorithms. It comprises supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Supervised learning trains models with known outputs and establishes a mapping between input and output variables. Unsupervised learning solves the mapping issue between input and output variables without labeled data. Semi-supervised learning combines supervised and unsupervised learning and uses both labeled and unlabeled data for pattern recognition. Reinforcement learning aims to achieve reward maximization or specific goals through learned strategies. The user layer displays the system's functional part and includes the user information processing center, situational diagnosis and prediction, learning path recommendation, and learner profile construction. The user information processing center primarily displays enrollment information. Situational diagnosis and prediction use a fusion approach to analyze the collected multimodal data and diagnose and predict learners' current learning situations and upcoming knowledge points. Learning path recommendation recommends paths that enable personalized, precise, and efficient learning based on the diagnosed and predicted information combined with knowledge graphs. Learner profiling analyzes learners' learning styles, knowledge and skill levels, learning motivation, etc., based on multimodal data, and continually updates and iterates to improve the accuracy of path recommendations.

Processes of MIALS to Facilitate Learners' Online Learning Engagement

This part includes four crucial aspects, namely the learner's motivation, learning style, emotional state, and level of knowledge and ability, all of which can be depicted in a knowledge graph or chart. To obtain this data, various sources are used, including operational logs, behavioral log data, text data, performance data, language data, emotional data, physiological data, and neural data, all of which provide valuable insights into the learner's engagement in the online learning process. The operational log data captures essential information such as login/logout time intervals, duration, and locations, while the behavioral log data, including resource and post learning frequency and duration, homework submission frequency and time, and post, reply, quote, and like frequency, offers insight into the learner's motivation and style. Additionally, the text data, including homework/testing content, post, reply, quote content and length, and chat room discussion content and length, provides a glimpse into the learner's knowledge and ability level. Performance data, on the other hand, comprises homework/test scores, posts, quotes, and likes, and is useful in understanding the learner's style, motivation, knowledge, and ability level. Language data, such as speech during live Q&A sessions and uploaded audio resources, reflects the learner's style, motivation, knowledge, ability level, and emotional state. Meanwhile, emotional data, which includes facial expressions during live Q&A sessions, and physiological data, such as neural and physiological data, offer additional information on the learner's engagement and emotional state. To analyze this data, the MIALS uses algorithms that track, diagnose, and analyze the learner's multimodal data in real time, providing a real-time engagement status of the learner. Behavioral log data, for instance, can serve as a basis for judging the learner's state, while text data uses text mining methods to extract high-dimensional features and interpret and represent text data. Performance data can be tracked in real-time using knowledge-tracking methods, such as Bayesian tracking algorithms and deep learning tracking algorithms. Furthermore, there are analysis methods for language data, emotional data, physiological data, and neural data that require preprocessing to eliminate noise and artifacts. The algorithms used for supporting multimodal analysis include Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs), among others. Learning diagnosis involves transforming learner process data and multimodal data into matrices or vectors with assigned weights. Bayesian knowledge tracking and deep learning knowledge tracking models are then used to predict the probability of learners' next learning engagement based on their profiles. Ultimately, learning recommendations are provided based on accurate recommendations for resources, paths, methods, etc., using content-based or proximity-based learning recommendation algorithms that evaluate relevance and similarity to the learner's profile or online learning engagement.

Conclusion

The MIALS, based on the collection, integration, and analysis of multimodal data, promotes learners' engagement in online learning. Detailed and scientific digital portraits of learners are created through multi-mode and multi-angle learning data acquisition. Real-time learning diagnosis is performed on learners' engagement data, knowledge tracking is continuously updated, and high-quality resources are provided. To achieve learner-centered online learning, personalized learning is a valuable area of exploration, considering students' development, subjectivity, and differences. The MIALS supported by multimodal data not only breaks the "undifferentiated teaching mode", but also solves the problem of low online learning engagement. However, the system is still in its initial stage, and some areas need improvement, such as the scientific interpretation of multimodal data, updating and applying technical algorithms, developing high-quality resources, and ensuring information security for learner data. This study proposes a framework for MIALS and provides a detailed explanation of how the system promotes learners' engagement in online learning through its working principles and modes. This contributes to improving learners' personalized learning, promoting their engagement, and reducing the probability of high dropout rates in online courses. It has a significant reference value for the application of IALS in the field of multimodal learning analysis and online learning. Future research needs to refine the learning phenomena represented by multimodal data and study them quantitatively using appropriate algorithms. Empirical research should also be conducted to explore further the application methods and implementation paths of the MIALS in the education field.

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