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REVIEW ARTICLE

Detailed study of learning behavior analysis approaches to tailor educational experiences based on individual preferences

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ABSTRACT

Over the past couple of years, it has been increasingly stressed that the traditional, standardized methods of educating people should be replaced with personalized forms of learning that suits a wide range of individual needs and requirements. The increasing availability of considerable amounts of data on learner interactions, combined with the advancements in artificial intelligence, machine learning, and educational technologies, has largely prompted this shift. Behavior analysis as a study (learning behavior analysis [LBA]) has become one of the key methods of studying the learning processes of learners and their interactions with educational tools, materials, and content. LBA allows the creation of adaptive systems that change instruction strategies and content delivery dynamically through an analysis of information on behaviors, cognitive processes, and affect. In this survey paper, an overview of the underlying principles, techniques, and technologies of LBA will be offered. It investigates multiple options such as the rule-based systems, supervised and unsupervised learning models, reinforcement learning, and educational data mining approaches. Furthermore, the paper discusses how these analytical methods can aid the personalization of the educational experiences by use of the learner profiling protocol, adaptive learning systems, intelligent tutoring environment, and real-time feedback systems. This study reminds us how powerful behavior-driven personalization can become by indicating the existing trends, challenges, and future trends that help learners better interact, perform, and like learning in different environments.

Key words: Adaptive learning, educational data mining, intelligent tutoring systems, learner profiling, learning behavior analysis, machine learning in education, personalized learning

INTRODUCTION

The large diversity of the needs, preferences, and learning speed of different learners in the same classroom has always challenged the traditional one-size-fits-all education system.[1] As the world is fast becoming digital and more organizations work with data and base their decisions on this information, education is gradually moving toward a new type of learner. This paradigm is based on flexibility, personalization, and adaptive experiences of learning, which favor individual differences better.

The growth of online learning environments, learning management system (LMS), and technology to deliver digital content has resulted in an unprecedented stockpile of data about the interactions between learners. This online trace offers priceless potential of learning in detail and examining the behavior of learning. In the era of globalization, when education should serve the needs of the learners with different cultural, educational, and socio-economic backgrounds, the necessity to receive a personalized learning experience seems to be more acute than ever.[2] Wherever student-based learning is constrained by the lack of human interaction, whether in a remote learning situation or a self-paced learning scenario, the need to have adaptive systems that could deliver real-time and individualized feedback is evident. This is why it is of vital importance to come up with educationally sensitive settings that would be sensitive to individual learner profiles, using preferences, abilities, and learning situations.

Personalized learning can be described as a type of learning instead of a program or a lesson that has been personalized to meet the requirements of the individual, his strengths, interests, and

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speed of learning.[3] It is interested in matching the teaching material, teaching styles, and assessment veterinary procedures to the individual learning profile.[4] There is also individualization, as opposed to standardized models; with personalized learning, every student follows a curriculum that fits their particular needs, hence resulting in an increased level of engagement, advanced knowledge, and higher academic achievements.[5] Furthermore, personalized learning is crucial in closing achievement gaps, fostering self-directed learning, and inclusive learning. It accommodates students with special needs or irregular learning styles so that everyone will be able to gain equal opportunities to the best learning experience.

The applied science of what is also known as learning behavior analysis (LBA) forms the heart of personalized learning in that it is a systematic gathering data on each learner that is analyzed and modeled in ways that help to understand and ensure an optimum learning experience.[6] Some of the behavioral measures that LBA can capture include: Time to complete tasks, tracks taken in platforms, test scores, engagement, happiness, and biometrics. With the help of data analytics, artificial intelligence (AI), and machine learning (ML) solutions, LBA can determine patterns and learnings that may be used to guide real-time adaptive interventions.[7] Based on these insights, the learning environment can be subsequently adapted by offering platforms to adapt in real-time to the strengths and weaknesses of the learners and providing features that allow for to detects of misconceptions or lack of engagement, as well as suggest personalized content or assistive features.[8] LBA, therefore, can be a key component of bringing about smart and customized learning systems that adapt to the behavior of the learner, rather than teaching by use of a fixed instruction system.

Structured of the Paper

In this study, I will describe foundations of LBA in the following manner: Section II is an overview of Foundations of LBA. Section III discusses approaches of LBA. Section IV outlines personalization of experience behavior, and Section V shows the challenges and limitations in learning analysis. Section V reviews literature and case studies, and Section VI concludes with future directions.

FOUNDATIONS OF LBA

LBA is one that relies on data and aims at examining the interaction of learners with educational materials, settings, and tools. It entails gathering, quantifying, and inferring the activity of learners to derive useful patterns indicative of cognitive reflection, affective nature, and learning task.[9] The final objective is to maximize education through matching educational experiences with the particular behavior profile of the learner.

The process of analyzing learning behavior patterns by recognizing behavior, describing sequences, diagnosing critical events, and predicting outcomes [Figure 1] ultimately generates insights for personalized learning.

It emphasizes a cyclical flow where behavior analysis informs event explanation, path revelation, and prediction refinement. Here are the key concepts central to LBA as follows:

- Learner modeling: The development of dynamic profiles of learners on the basis of behavioral patterns
- Engagement metrics: Numbers of engagement, attention, and effort
- Interaction tracking: Real-time monitoring of the actions of learners, for example, clicks, scrolling, and the time they spend on tasks
- Adaptation mechanisms: Employing the commands of behavior to regulate learning pathways as well as content delivery.

LBA is an interdisciplinary study that crosses educational psychology, data science, human-computer interaction, and AI, and allows personalized and intelligent learning systems.

LBA enables personalized education by examining how learners interact with content and tools.[10] It uses behavioral data to build learner profiles, track engagement, and adapt instruction in real time. Combining insights from psychology, AI, and

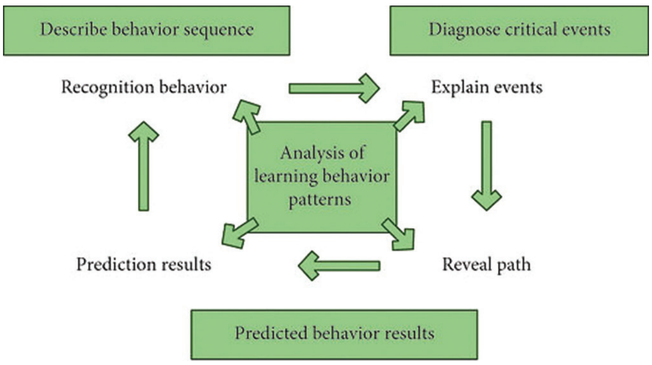

Figure 1: Learner behavior analysis model framework

data science, LBA enhances learning by aligning educational experiences with individual behavior patterns.

Types of Learners and Learning Styles

Learners can be categorized based on their preferred modes of processing information, often described using learning style models. Visual, auditory, read/write, and kinesthetic learning styles are the four main categories recognized by the VARK model. Another common framework is Kolb's experiential learning theory, which outlines styles such as converges, diverges, assimilators, and accommodators. Understanding these types helps educators and systems tailor content delivery to suit individual learning preferences. However, it is also important to note that learning styles are dynamic and may evolve based on context, prior experience, and exposure to diverse instructional techniques. Learning behavior is difficult to comprehend without the examination of multiple aspects of learning activity.[11] All these behavior can normally be classified into three major categories:

Cognitive behaviors

These are associated with the cognitive aspects of learning, which include understanding, reasoning, memory, and problem-solving. The process of guessing cognitive behavior can be made based on comprehensive work time, quiz marks, revision rates, and the error rate. For example, spending a lot of time on a question can indicate either deep processing or confusion.

Affective behaviors

These are the emotional sets that the learner is in and their attitude toward things, for example, motivated, frustrated, bored, and nervous. The key importance of affective behavior analysis lies in its ability to identify cases of disengagement or obstruction in the learning process caused by emotions. It can be derived from facial expressions, tone of voice, keystroke dynamics, or physiological reactions, such as cardiac activity and skin conductance.

Behavioral patterns

These methods involve visual elements such as navigation routes, clicks on material, time-on-task, video interaction trends, and participation in forums. These behavioral data include direct information on the level of engagement and the learning strategies a learner applies, whether they are skimming or exploring content.

The three kinds of behavior analyzed thoroughly permit a holistic understanding of the learner's nature, allowing for more targeted personalization and intervention.

Tools and Technologies Used in LBA

LBA can be successfully implemented using a number of various tools and technologies. These include:

- Learning analytics platforms: Learning analytics platforms, such as Moodle Analytics, blackboard predict, and open learner models, enable real-time tracking and visualization of learner activity data.
- AI and ML: Decision trees (DT), neural network (NN), clustering, and reinforcement learning (RL) algorithms are able to detect patterns, classify the type of behavior, and predict the outcome of a learner.
- Educational data mining (EDM): Involving the procedures of knowledge mining in educational databases, EDM methods assist in segmentation of the learners, prediction of drop-out, and recommendation systems.[12]
- Eye tracking and gaze analysis: The software and technology, such as Tobii or Web Gazer, can be used to identify where a learner is looking on the screen, which indicates attention and engagement
- Sensor technologies and wearables: Smart watches, electroencephalogram bands, and other biosensors are used to gather information related to stress, fatigue, and emotional conditions.

Sources of Learning Data

Analysis of the learning behavior depends on the variety of rather sources of data that record both the direct and indirect measure of student engagement. The most important sources are as follows:

- LMS: LMSs offer detailed records of learner activity, including the number of logins, frequency of use of various resources, posts in the discussion forums as well as assignments. These statistics are useful in the study of the level of engagement and academic patterns.

- Eye tracking: Eye tracking technologies present a range of information about where learners focus their attention and which areas their visual focus is directed using the patterns and fixation points. This data indicates the way learners consume on-screen information and helps to analyze cognitive processes and attention processing.
- Clickstream data: The process of clickstream analysis includes monitoring the movement of the users with the mouse, scrolling direction, navigational patterns, and duration on the different learning digital components. It aids in the unveiling of behavioral trends and interaction tactics even in the course of learning.
- Biometric and wearable devices: These kinds of tools use physiological measures of affects which include heart rate variability, skin conductance, and facial expression to estimate the affective state and the level of stress. This kind of information enhances emotional consciousness and affective modeling of learning systems.
- Self-reports and surveys: Self-assessment as made by the learners gives the subjective and useful data on levels of emotions, motivations, learning preferences, and self-control mechanisms. These answers supplement observational feedback by psychological and reflective input.

Incorporation of such different sources of data enables the development of responsive and smart education systems. Such systems make learning more effective, more personal, and much more engaging because they tailor instruction to individual student profiles.

APPROACHES FOR LBA

The section addresses a wide variety of the methods that can be applied to the analysis of the learning behaviors, including conventional statistical models, ML methods, deep learning (DL) architectures, and their combinations. LBA takes advantage of these analysis and computation capabilities to discover patterns in the data about learners and make meaningful inferences that accommodate adaptive interventions. Such means as rule-based systems, supervised/unsupervised learning, and EDM provide different possibilities in view of applicability, flexibility, and reusability. Both methods introduce their strengths to the attainment of explicit educational purposes in the increasing competitive and differentiated academic settings.

Rule-Based and Heuristic Methods for LBA

One of the first LBA methods employed is the rule-based and the heuristic approaches. These algorithms can read the actions of the learners and results based on pre-determined rules and logic created by experts. As an example, one rule may be considered that flags a student to be at-risk when there is a series of three quizzes with more than 50% being a at-risk rating.[13] Heuristic systems often employ simple DT, fixed thresholds, or basic logical conditions to trigger feedback, categorize learners, or recommend instructional materials. While not adaptive, these methods offer interpretable and quick assessments based on clear criteria. These are the rules which are as follows:

- It is interpretable and transparent, hence also good to be used by educators.
- Simple to get working, particularly where an LMS does not have a sophisticated analytics infrastructure.

Nonetheless, rule-based systems are not so flexible and scalable. It is not always effective on dynamic or very large systems because they derive their decision-making power from fixed rules and do not adapt to new information.

ML and DL Models for LBA

ML and DL are powerful approaches for modeling complex learner behavior due to their scalability and ability to adapt to diverse educational contexts.[14] These data-driven techniques leverage both historical and real-time data to detect patterns, make predictions, and support adaptive learning environments. The three primary categories of ML algorithms are as follows: Supervised learning, which utilizes labeled data to predict specific outcomes; unsupervised learning, which identifies hidden patterns or groupings within unlabeled data; and RL, which learns optimal actions through a trial-and-error process within defined environments, progressing from a starting state to a goal state [Figure 2]. Each category is suited to distinct analytical tasks such as classification, clustering, and sequential decision-making in educational settings.

ML and DL provide powerful and flexible models to analyze the intricate learner behavior through deriving the trends, making predictions and customizing the learning experience. These models can cover various education-related tasks, such as classifying the performance of students and identifying their engagement rates and setting the optimum learning paths through sequencing decision-making with techniques of supervised, unsupervised, and RL. They are necessary tools in enhancing intelligent and responsive educational system due to their ability to be scalable and adapt to real-time needs.

ML models for LBA

LBA ML models assist in identifying the patterns in the learner data to make predictions, detect at-risk students, and personalize learning. Such models are DT, support vector machines (SVM), K-nearest neighbors,[15] and ensemble techniques, which analyze structured data to inform flexible and data-driven educational interventions.

Supervised learning

The goal of supervised learning is to train a model with known output using labeled data sets. Most often, supervised techniques are as follows:

- DT: Simple to read yet applicable in extracting rules in the categorization of behavior
- SVMs: This is efficient in a binary problem such as engagement detection or the prediction of dropouts

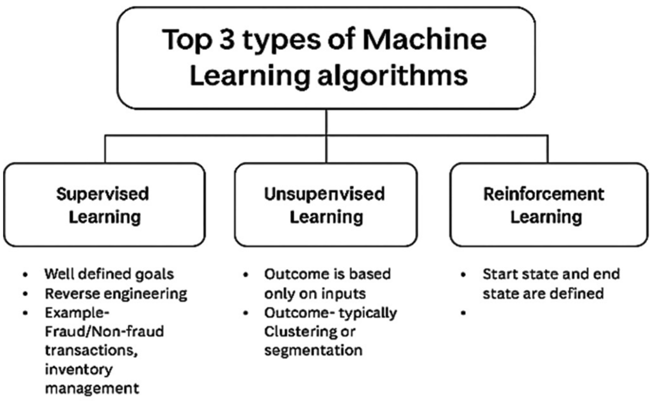

Figure 2: Types of machine learning algorithms

- Random forests: It offers firm ensemble learning to feature significance in the learner models
- NNs: They are used in solving complex problems, such as predicting the outcome of living organisms, but they require vast amounts of data.

Such prognostic measuring sticks have been used to predict student performance, the level of engagement, and the likelihood that they will complete the course.

Unsupervised learning

Unlabeled data involves the use of unsupervised learning techniques to reveal patterns that are hidden in it. Such are particularly useful in segmenting and profiling learners.

Here are the techniques are as follows:

- Clustering: Learners are grouped or clustered based on similarities in the way that they behave and meaningful personas are created.
- Dimensionality reduction: Aids in representation of behavioral patterns and decreases in noise within high-dimensional data of learners.

Unsupervised classification permits exploratory study and distinction of new behavior of patterns in the cases with no prior classification.

RL in adaptive systems

The most recent applications of RL models are seen in adaptive learning, where the system learns the best teaching procedure through trial and error. RL agents are in communication with learners and receive rewards or punishments based on the learners' engagement, accuracy, or enhancement. These are reinforcement techniques for adaptive system as follows:

- RL is applicable when it comes to dynamic recommendations of certain content, order of activities, and custom feedback loops.[16]
- Examples include intelligent tutoring system (ITS) that adjusts its teaching approach over time depending on the behaviors of the individual learners.

RL provides one way to support the vision of fully autonomous, self-improving educational systems that adapt to real-time, and individualized requirements.

DL approaches

DL excels in modeling complex, high-dimensional learner data, especially time-series and multimodal input. Here are the DL approaches are mentioned in below:

- Convolutional NNs (CNNs): Visual learning behavior, including the interpretation of heatmaps showing screen gaze, facial expressions, and handwritten inputs, are frequently subject to CNN analysis.[17] Their ability to extract spatial hierarchies from visual data makes them effective in understanding learner engagement through visual cues.
- Recurrent NNs (RNNs): Learners' interactions, including clickstream data, navigation patterns, and sequential material access, can be captured by RNNs due to their sequential data processing design. Their memory structure allows modeling of patterns over time.
- Long short-term memory networks (LSTMs): LSTMs are a subset of RNNs that excel in learning temporal dependencies.[18] They are commonly applied to student activity logs, helping to uncover behavioral trends over extended learning sessions.
- Transformers: As a state-of-the-art architecture, transformers excel in modeling contextual and sequential dependencies using attention mechanisms. In educational contexts, they are applied to analyze complex patterns such as discourse-level interactions, learner attention shifts, and contextual relevance across learning materials.

EDM techniques for LBA

EDM is a narrow field that emphasizes using data mining techniques in education contexts to study a student learning behavior and enhance student learning.[19] Here are the key EDM techniques include:

- Classification: This is applied to profile students by historical behavior
- Regression: Makes predictions of continuous variables like the expected scores in a test
- Association rule mining: Posits common behaviors and those that often appear together, for example, students with misses in readings tend to fail in the quizzes
- Sequential pattern mining: Examines any temporal sequence in action, such as a sequence of topic search, or disengagement phases
- Text mining: Text mining is used on open-ended answers, posts on discussion boards, and comments to measure understanding, attitude, or type of collaboration.

EDM integrates knowledge both in the area of educative theory and the traditional data mining to provide instructional decision-making by instructors and designers, as well as adaptive systems.

TAILORING EDUCATIONAL EXPERIENCES BASED ON INDIVIDUAL PREFERENCES

Personalizing learning environments for students entails adapting lessons to each student's own personality, areas of interest, and academic requirements.[20] By leveraging advanced educational technologies informed by LBA, it becomes possible to dynamically adjust instructional content, pacing, and support mechanisms.[21] This customization fixes this by helping increase learner interaction, better academic results, and allowing greater analysis of learning trends. Important components of such an approach are adaptive learning systems, intelligent tutoring, real-time feedback, and individualized delivery of educational content that leads to more meaningful and effective educational outcomes.

Tailoring Content Based on Learner Profiles

Profile-based learner models are representations of the learning behavior, prior knowledge, cognitive capabilities, preferences, and past learning experiences of a particular individual. The initial stage is to implement personalization through examining these profiles to provide the most pertinent and competent information to every learner.[22] The most important ones are the content recommendation engines[23] that propose resources, such as videos, readings, or assignments, depending on the learning styles and performance patterns, individualized learning paths that organize curriculum by a learner-specific sequence of what they have to learn and are able to learn or language and difficulty adaptation that adjusts the difficulty of the content read-only language. The ability to adapt to the learner characteristics increases the engagement of the learner, the efficiency of learning and eliminates the redundancy and cognitive overload is below:

- Content recommendation engines: Make recommendation of learning materials (videos, readings, and exercises) according to their performance patterns, learning styles (visual, auditory, and kinesthetic), or mastery of talent
- Individual learning paths: The curriculum can be structured based on the strengths and weaknesses of learner therefore, he/she can move at his/her pace
- Language and difficulty adaptation: Vary the difficulty of content and language by level, by level of comprehension or by familiarity with a subject domain.

Adaptation to the characteristics of a learner not only increases relevance and motivation but also leads to the efficient use of time and mental effort, eliminating redundancy, and saturation.

Adaptive Learning Systems

Adaptive learning systems dynamically adjust the delivery of instruction based on student behavior and performance[24] using real-time data and algorithms driven by AI. These systems monitor the student's development in real time and modify different aspects of the learning process appropriately.

- Dynamic difficulty adjustment: Automatically reduces or increments the degree of questions or activities according to the accomplishments of learners
- Re-routing path: When one fails in mastering a concept, the system can redirect to additional materials or an alternative description
- Skill mastery tracking: Helps tie learning objectives to performance and ensures that each step of the learning process covers each skill in great depth before moving on to the next.

Such examples are described as platforms, such as dream box, assessment and learning in knowledge spaces, and smart sparrow, where math or science lessons are adapted along a learning path. The systems facilitate the deeper learning of a learner by making sure that every learner goes through lessons at the appropriate level at the appropriate time.

ITS

The ITS are artificially intelligent programs used in education that imitates the roles of a human tutor in providing tailored instructions or advice.[25] They combine the content knowledge, pedagogical content knowledge, and knowledge of how learners behave, creating an interactive and responsive learning environment. Here are the key features:

- Individual hints and scaffolding: Helping learners when they have troubles
- Error diagnosis: The correction of misconceptions and provide defensive explanations
- Conversational interfaces: Interacting in a natural language (e.g., through chatbots) with learners through conversational interfaces
- Learner modeling: Maintaining the system and continuously revising the model that captures the image of the learner to make improvements on the teaching recommendations.

ITS systems, such as the auto-tutor, Carnegie learning, and cognitive tutor, have been shown to have identified learning improvements of a comparative margin in several different subjects through support similar to human tutoring.

Real-Time Feedback and Intervention Mechanisms

Feedback is a critical component of effective learning, and it should be timely, specific, and personalized. Real-time feedback systems allow learners to instantly recognize and correct their mistakes, assess their performance, and stay engaged throughout the learning process. These systems support continuous improvement and adaptive interventions. Common types of feedback include corrective feedback (highlighting errors and providing the correct response), reinforcement feedback (encouraging positive behavior), elaborative feedback (offering detailed explanations), and predictive feedback (anticipating learner needs based on behavior patterns) are as follows:

- Performance feedback: Successful response to answers on the quiz, completing assignments or exercises. For example, Correct. It did not make any mistakes when using the formula
- Process feedback: More information about how to deal with an issue, for example, is to divide the problem into small sub-problems

- Behavioral feedback: Warnings of lack of action, distraction, or disengagement, for example, it appears to be inactive,
- Emotion-aware feedback: When advanced technology is present, the presentation of emotional support messages or encouraging hints may be induced by facial or physiological statistics.

In tailoring educational experiences based on individual preferences through learner profiling, adaptive systems, intelligent tutoring, and real-time feedback significantly enhances the personalization, efficiency, and effectiveness of learning. By dynamically adjusting content, difficulty levels, instructional strategies, and support mechanisms, these approaches cater to each learner's unique needs, fostering engagement, improving academic outcomes, and enabling timely interventions. The integration of AI and LBA ensures that educational experiences are not only responsive and relevant but also supportive of continuous growth, motivation, and meaningful learning trajectories.

CHALLENGES AND LIMITATIONS IN LBA

LBA faces key challenges, including poor data quality, limited access to diverse learner datasets, and difficulties in interpreting complex models. Many systems struggle to generalize across different learners and educational contexts. In addition, achieving real-time, scalable, and adaptive solutions remains a technical hurdle, limiting the broader adoption of LBA in dynamic learning environments. There are some main challenges with limitations in LBA which are as follows:

- Data quality and accessibility: High-quality, diverse, and representative learner data are crucial for effective analysis. However, issues such as missing values, noise, bias, and restricted access to real-time or large-scale educational datasets hinder the development of robust learning behavior models.
- Models' accuracy and transparency: The decision-making process of many sophisticated models is opaque to teachers because they function as "black boxes," especially those built on top of DL. Trust and practical acceptance in educational contexts might be hindered by this lack of transparency.
- Generalization across: Generalization across contexts and learners models trained on specific populations or environments often struggle to generalize to different educational contexts, learner demographics, or instructional formats, limiting their broader applicability on texts and learners models trained on specific populations or environments often struggle to generalize to different educational contexts, learner demographics, or instructional formats, limiting their broader applicability.
- Scalability and real-time adaptation: Implementing scalable systems that can adapt to large cohorts of learners and respond in real time poses computational and design challenges. Balancing personalization with system responsiveness and cost-efficiency remains a key limitation.

LITERATURE REVIEW

The literature review highlights the use of AI and ML to personalize education through behavior analysis, early intervention, and adaptive content delivery. Studies explore tools like GenAI for lesson planning and ML-based early warning systems for at-risk students. Ethical concerns, scalability, and cross-disciplinary applicability emerge as key future directions. Table 1 summary of key literature on AI and ML approaches for personalized LBA is given below.

Garcia-Suarez *et al*. contribute to knowledge by illustrating AI's capacity to align educational strategies with individual needs, fostering better comprehension and motivation. It also brings out the ability of AI to revolutionize conventional teaching by making it scalable and inclusive. Further studies will explore the scale of these plans to be implemented in different fields of study, and also, the effect it will have in the long run to give a guideline of how AI can be used in the education systems of the world.[26]

Liu *et al*. came up with an emotionally intelligent technology that could recognize and respond to human emotions. The multi-task learning challenge involves the s-Aff-Wild2 database and is organized as the 7th affective behavior analysis in-the-wild competition to further develop such a domain. The participants must come up with a framework which would carry out valence-arousal estimation, expression recognition, and action

Table 1: Summary of key literature on AI and machine learning approaches for personalized learning behavior analysis

Reference	Study focus	Approaches	Strategies	Strengths	Limitations and future work
Garcia-Suarez *et al*. (2025)	AI for personalized education	AI-driven personalization	Tailoring strategies to learner need.	Enhances comprehension and motivation; scalable and inclusive	Broad implementation yet untested, investigate applicability across disciplines; assess long-term effects
Liu *et al*. (2025)	Emotion-aware AI in education	Multi-task learning (s-Aff-Wild2, ABAW)	Progressive multi-task framework (Valence-Arousal, Expression, AU detection)	Emotion recognition improves user interaction and learning adaptation	Complex model design and facial expression data dependency, enhance task synergy; extend applications in real-time emotion-sensitive learning environments
Abu-Issa *et al*. (2024)	Adaptive student modeling	Learning preference and skill profiling	Interactive platform-based quizzes to detect styles and misconceptions	Supports collaborative learning; creates personalized profiles	Dependent on user engagement and accuracy of self-reports, expand profile dynamics and incorporate adaptive interventions.
Yi, *et. al.* (2024)	Performance prediction in blended learning	SMOTE-XGBoost-FM, Z-score normalization	Correlation analysis between behavior and performance	High predictive accuracy; identifies key behavior-performance link	Lacks real-time feedback; model complexity. Integrate real-time analytics for dynamic feedback loops
Yang *et al*. (2024)	Early warning system for struggling students	ML classifiers (LR, DT, RF, and SVM)	Real-time LMS data monitoring, feature selection and standardization	Enables early intervention; multi-model comparison	May require significant data cleaning and processing, improve model generalizability, scale across platforms
Karpouzis *et al*. (2024)	GenAI-assisted lesson planning	NLP-based GenAI with mega-prompts	Educator-customized prompts for tailored lesson plans	High adaptability, strong feedback loop; practical for teachers	Requires continuous updates and training
Dhananjaya *et al*. (2024)	E-learning and recommendation systems	Literature review of 60 studies	Collaborative filtering, content-based, ML-based recommendations	Broad coverage of recommendation tech; identifies critical challenges	Highlights infrastructural and user engagement issues, Expand cross-cultural adaptability and automated feedback mechanisms. Proposes future tools such as Fluxy AI, Alter Ego, and Twin tech.

AI: Artificial intelligence, ABAW: Affective behavior analysis in-the-wild, AU: Action unit, LR: Logistic regression, DT: Decision tree, RF: Random forest, SVM: Support vector machines, ML: Machine learning

unit simultaneously proposed a gradual multi-task learning framework that takes full advantage of the unique attentions of each task regarding facial emotion features.[27]

Abu-Issa *et al*. combine learning preferences with competence levels to construct an effective student model. By tracking the user's preferred methods of learning, current knowledge, and pinpointed gaps in understanding, they can create a detailed profile of each student. Participation in online quizzes testing both knowledge and personality traits provides the data. To further facilitate collaborative learning, a student can share their profile with other students.[28]

Hao this study, in a blended learning environment, students' online learning behavior data is processed using the Z-score data standardization approach. The correlation analysis method then determines the relationship between each learning behavior feature and performance. After that, they use the SMOTE-XGBoost-FM model to forecast students' academic performance according to their behavioral traits; subsequently, they use the results of this performance prediction to guide instructional interventions and changes that yield positive outcomes for students. It was confirmed that, when considering the impact of online learning behavioral aspects on academic success, there was the highest association between homework scores and performance.[29]

Yang *et al*., provide a system that analyses student learning behavior in real-time and uses ML to predict which students could have trouble learning and send out timely warnings based on that data. To track things such as class participation, homework turned in, and online learning activities, the system makes use of a LMS and an online learning platform. The models are trained and evaluated using logistic regression, DT, random forests, SVMs, and feature reduction and standardization after data cleaning.[30]

Karpouzis *et al*., present an AI application that uses powerful NLP to help teachers create personalized lesson plans. One cutting-edge aspect of the program is the “interactive mega-prompt,” a thorough inquiry system that lets teachers input data about their classrooms, including student demographics, learning goals, and preferred teaching methods. The GenAI will use this information to create personalized lesson plans. A large-scale methodology was used to evaluate the tool’s effectiveness. The methodology included both quantitative and qualitative criteria, and it covered a wide range of subjects and educational levels. Educators received constant feedback through a direct evaluation form.[31]

Dhananjaya *et al*., explore the possibility of using e-learning technology and individualized recommendation systems in teaching. It analyzes 60 articles of several well-entrenched databases and discovers the types that different systems of recommendation use collaborative and content-based techniques, and nowadays, there is a swing toward ML. Nevertheless, the existing personalized recommendation system has such limitations as the failure to understand the content, student discontinuity, language barrier, and lack of clarity in choosing the study material, as well as poor infrastructure and finance. Among the new digital technologies proposed to handle those issues by their review are Fluxy AI, twin technology, AI-based virtual proctoring, and Alter Ego.[32]

CONCLUSION AND FUTURE WORK

The survey paper highlights that LBA is imperative in the generation of personalized learning experiences. By examining key concepts, data sources, analytical methods, and adaptive learning systems, it is evident that aligning educational strategies with individual learner behavior holds great potential to transform modern education. From rule-based heuristics to advanced ML models, these techniques enable real-time interpretation of cognitive, affective, and behavioral patterns, making learning more inclusive, engaging, and effective through ITSs, dynamic feedback, and personalized content delivery.

Future research should explore the integration of real-time biometric and emotion-aware data to deepen personalization, while also addressing the needs of multilingual, culturally diverse, and neurodiverse learners to enhance accessibility and equity. As these systems evolve, ethical considerations such as reducing bias and safeguarding privacy must remain a priority. The fusion of emerging technologies like augmented reality/virtual reality, wearables, and generative AI can further enable immersive, contextually aware environments, ultimately guiding the development of more humane, responsive, and holistic educational ecosystems that foster self-regulated and lifelong learning.

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