Volume 2 No 6, 2026
Journal of Global Research in Multidisciplinary Studies (JGRMS)
Review Paper
Available online at https://saanvipublications.com/journals/index.php/jgrms/index

A Survey on Interpretable Machine Learning Techniques for Student Adaptability Prediction in Educational Systems

Sushmita Gour
M_Tech Scholar
CSE-TIT (Excellence)
Baroda M P
sushmitagour85@gmail.com

Kamlesh Raghuvanshi
Assistant Professor
CSE-AIML-TIT (Excellence)
Bhopal M.P
raghu.kamlesh82@gmail.com

Ram kumar Sahu
Assistant Professor
CSE-AIML TIT (Excellence)
Bhopal M.P
ramkr.sahu@gmail.com

***Abstract*—Education is an important part of growing knowledge, skills and adaptability in today's rapidly evolving society. The digital revolution has led to the widespread adoption of online learning platforms, smart tutoring systems, and data-driven learning environments in education, enhancing learning effectiveness and accessibility. This is because the difficulty of predicting students' adaptability has become an important research topic, helping to understand learning difficulties, improve learning outcomes and personalize learning. This survey explores how interpretable machine learning (IML) techniques can be used to predict student adaptability in the context of education. It explores machine learning and deep learning models such as Decision Trees, Random Forests, Support Vector Machines, XGBoost and Long Short-Term Memory (LSTM) networks for learning student behaviour, engagement and learning patterns. Furthermore, the paper explores the concept of Explainable Artificial Intelligence (XAI) methods (including SHAP analysis, LIME, feature importance analysis, and rule-based explanations) that contribute to making AI in education more transparent and trusted. In smart educational environments, the results indicate that applicable AI methods enhance the adaptive learning approaches, timely interventions, provide individual assistance to students, and provide clear analytics.**

Keywords—Interpretable Machine Learning, Explainable AI, Student Adaptability, Educational Systems, Learning Analytics, Educational Data Mining.

.

I. Introduction

Education is a key factor in the generation of knowledge, skills, critical thinking and social development of the society. They offer frameworks for learning that support learning, prepare students for the next phase of their learning journey, and foster lifelong learning. With the rapid development of technology, the traditional education model has been changed to flexible and technology-based education model. The introduction of new teaching methods, online teaching resources and virtual classrooms has improved the quality of the teaching and learning process from various angles, including improved access and efficiency [1][2]. In smart learning, personalized and interactive learning environments are created using adaptive technology, AI and data analytics. Online learning and blended/hybrid learning platforms have also become more important because they allow students to learn remotely, foster collaboration between students and create opportunities for access to learning regardless of social class and geographic location.

Adaptability plays an important role in the current education systems as it enables students to adapt to the new learning environment, learning technologies and teaching methods [3]. Due to the ever-increasing adoption of online and digital learning platforms, it is also important to prepare for learning in virtual spaces to maintain continuity and engagement in the learning process [4]. The ability of adaptation in behavior and cognition enables students to cope with learning difficulties, to problem-solve and adapt positively to changes in learning and technology [5]. Effective adaptability also has an impact on academic achievement, student engagement and retention, by enhancing participation, decreasing learning challenges and promoting long-term educational outcomes.

Machine Learning (ML) plays a vital role in the present-day education by introducing various advantages for both teachers and students, such as enhancing the teaching process, evaluating students, and creating personalized learning experiences [6]. Patterns of student behavior, interaction, academic performance and engagement in digital environments can be analyzed using ML algorithms, which can then be used by educators to give instant feedback to students, be able to detect gaps in their learning, and support adaptive learning according to the needs of each student [7]. The developments also improve the assessment systems, intelligent systems can generate individualized questions to evaluate understanding and critical thinking skills more effectively. For technology-based learning, ML enables teachers to monitor students' learning and to create interactive and real learning moments. Another crucial role is played by Explainable Artificial Intelligence (XAI), which enhances transparency in machine learning predictions and decisions in educational settings by offering clear explanations [8]. Furthermore, ML can be used for the development of flexible education systems that can be accessed in various contexts, including resource-constrained contexts. Yet there are various issues that need to be addressed before the full-scale implementation of ML-based technologies in education, such as ethical, data privacy, fairness, and accessibility.

A. Structure of the Paper

This paper is structured as follows: Factors influencing adaptability and various educational learning environments are presented in Section II. Section III presents theories and methods of ML for predicting student adaptability. In section IV, the focus is on interpretable ML and XAI methods in education. The next section, V, presents a review of the literature related to interpretable educational prediction systems. Finally, Section VI summarizes the survey and suggests research areas for the future.

II. Fundamentals of Student Adaptability Prediction

Adaptability in Education is the ability of learners to adjust to the new education contexts, pedagogy and technology. Flexibility has become a vital trait in the learning process for achieving at school, involvement in school activities, and student learning, in particular with the shift to online and blended learning environments [9]. The development of digital technology has reshaped the traditional educational system into more flexible and technology-based systems. The terms 'Education 2.0', 'Education 3.0', and 'Education 4.0' illustrate the growing trends of online platforms, interactive tools, and smart educational technologies [10][11]. Such innovations enable students to have access to learning materials at any time and to make personalized learning possible. In recent years, however, Educational Data Mining (EDM) and ML have become important for dealing and analyzing student data such as academic performance, participation and behavioral patterns. All of these technologies could be utilized to identify learning patterns, predict student attainment and early red flag students at risk. In addition, ML-based educational systems have the capacity to enhance adaptive learning by delivering personalized recommendations and facilitating decision-making in the context of today's education systems. The following are some of the major ideas of student adaptability:

- **Academic adaptability:** Academic adaptability is the ability of a student to adjust to various academic settings, learning styles, course demands, and educational problems in an effective manner [12]. It covers managing study strategies, maintaining learning performance, adjusting to new technologies and reacting positively to changes in curriculum and teaching style. Students who are academically adaptable tend to be more engaged, have better problem-solving skills, and have better academic outcomes.
- **Psychological and social adaptability:** Psychological and social adaptability is the student's capacity to adjust his/her emotional and social life to an educational environment. This involves handling stress, developing self-confidence, developing positive relationships with teachers and peers, and being active learners. Good adaptability helps to enhance communication, emotional state, collaborative work, and study results [13]. It also helps in the student's engagement, social integration, and adaptation to new learning environments and technologies within modern inclusive classrooms.
- **Adaptability in online learning environments:** Adaptability in online learning settings is the ability of a student to adjust to the online settings, virtual classroom, and technology-driven learning approach [14]. Students who are adaptable will be able to effectively utilize online tools, stay engaged, maximize learning and enhance satisfaction in online learning.

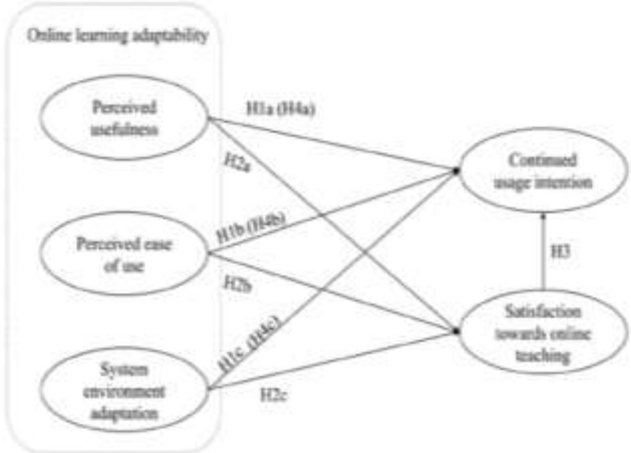

Fig. 1. Online learning adaptability factors

As shown in Fig. 1, the use of online learning platforms is positively affected by student satisfaction with the materials and their adaptability. The model emphasizes the perceived usefulness, perceived ease of use, and system environment adaptation as factors influencing student interaction, teacher satisfaction with the system and even their desire to return to the online learning platforms.

A. Types of Student Adaptability

Students can be classified into different types depending on how they cognitively, behaviorally, emotionally and socially react to an evolving education environment.

- **Cognitive adaptability:** A cognitive adaptable student is one who is able to change his or her thinking and learning approaches to fit different learning scenarios. This ability will help students working in new learning contexts understand complicated ideas such as [15] and adjust to changes in teaching approaches or educational technologies.
- **Behavioral adaptability:** Behavioral adaptability involves changing attitudes, actions and interactions in various educational environments [16]. Good behavior flexibility enhances classroom involvement, interaction with peers, socialization, communication with teachers and effectiveness of learning.
- **Emotional adaptability:** A student's ability to control their emotions, deal with academic stress and remain motivated despite challenging learning environments. This skill enables students to maintain a positive attitude, withstand stress and adapt to changes in their learning environment.
- **Social adaptability:** Social adaptability is defined as the student's ability to interact and work with teachers, peers and learning community in a range of educational settings. This ability helps develop excellent communication, teamwork and an ability to function in various social and cultural environments.

B. Factors Affecting Student Adaptability

Adaptability among students relies on academic, technological, social and psychological factors which affect the students' ability to adapt to new learning contexts, to use new technologies and to handle academic challenges.

1) Learning Environment

Learners' adaptability, engagement, participation and performance in the learning environment is strongly affected. Supportive and flexible classrooms promote communication, collaboration and active learning, and effective teacher guidance and adaptive resources enhance the overall learning process.

2) Internet Accessibility

Internet accessibility is essential for students to be successful in online and digital learning. A secure connection allows them to participate in the classes, utilize the resources and fully immerse themselves in their studies. A weak connection can also present issues that can interfere with learning and negatively impact academic achievement.

- Students' digital learning is directly influenced by having reliable internet.
- The poor internet connection poses difficulty in taking online classes, accessing learning resources and completing homework.
- In rural areas or from a low socioeconomic background, students often face connectivity problems which significantly impact learning continuity.
- Digital materials that can be accessed and internet speed that can be accessed enhances access and learning environment.

3) Family and Socioeconomic Conditions

Familiarity with the socio-economic and family background of students also has an impact on the adaptability and school performance of the students [17]. Well-off students are more likely to be able to access the resources of schools, to be able to access the internet and have parents' support, which makes them more motivated and have positive learning behaviour. However, economic insecurity and scarce resources can have adverse impacts on adaptability, learning, and emotional health.

4) Motivation and Engagement

Motivated students are more likely to adapt successfully to new educational systems and learning technologies [18]. Active participation in discussions, assignments, and collaborative activities improves learning confidence and academic persistence, while low motivation can reduce participation, performance, and adaptability to changing educational environments.

5) Mental Health and Stress

Mental health strongly affects student adaptability and learning effectiveness. Academic pressure, stress, workload, and social isolation can negatively impact concentration, decision-making, and learning behavior. Emotional support, counseling services, stress-management strategies, and healthy learning environments help improve psychological well-being and adaptability [19].

6) Digital Literacy

Digital literacy refers to a student's ability to effectively use digital technologies, online platforms, and educational software for learning purposes. Students with strong digital skills can easily navigate virtual classrooms, online assessments, and e-learning resources [20].

C. Online Learning Adaptability

Online learning adaptability refers to a student's ability to effectively adjust to digital learning environments, virtual classrooms, and technology-based educational systems. It involves managing online learning challenges, maintaining engagement [14], using digital resources efficiently, and adapting to evolving instructional methods and remote learning activities.

D. Educational Data Mining and Learning Analytics

EDM and Learning Analytics (LA) are important approaches used to improve student adaptability and learning outcomes in modern educational systems [21][22]. These technologies use educational data, machine learning, and analytical techniques to identify learning patterns, predict student performance, and support personalized learning environments. Additionally, they assist teachers in keeping an eye on student participation, identifying at-risk students, and offering prompt academic assistance.

1) Educational Data Mining (EDM)

EDM applies data mining and ML techniques to analyze educational data such as student grades, attendance, assessments, and learning activities [23]. EDM aims to uncover meaningful patterns and predict student performance to optimize teaching and learning, and it supports four core types of applications in digital learning environments.

2) Learning Analytics (LA)

LA is the data-driven research method, whose core function is to collect, analyze, and interpret learner-related data to understand and optimize learning processes [24]. Its data sources cover educational interaction data such as those from learning management systems and student surveys. It can assess student behavior and support educational decision-making, with its core goal being to improve learning effectiveness through approaches such as personalized feedback [25]. It differs from educational data mining, which focuses on extracting potential patterns in datasets, and places greater emphasis on optimizing learning experiences through real-time feedback.

III. Fundamentals of Student Adaptability Prediction

Adaptability in Education is the ability of learners to adjust to the new education contexts, pedagogy and technology. Flexibility has become a vital trait in the learning process for achieving at school, involvement in school activities, and student learning, in particular with the shift to online and blended learning environments [9]. The development of digital technology has reshaped the traditional educational system into more flexible and technology-based systems. The terms 'Education 2.0', 'Education 3.0', and 'Education 4.0' illustrate the growing trends of online platforms, interactive tools, and smart educational technologies [10][11]. Such innovations enable students to have access to learning materials at any time and to make personalized learning possible. In recent years, however, Educational Data Mining (EDM) and ML have become important for dealing and analyzing student data such as academic performance, participation and behavioral patterns. All of these technologies could be utilized to identify learning patterns, predict student attainment and early red flag students at risk. In addition, ML-based educational systems have the capacity to enhance adaptive learning by delivering personalized recommendations and facilitating decision-making in the context of today's education systems. The following are some of the major ideas of student adaptability:

- **Academic adaptability:** Academic adaptability is the ability of a student to adjust to various academic settings, learning styles, course demands, and educational problems in an effective manner [12]. It covers managing study strategies, maintaining learning performance, adjusting to new technologies and reacting positively to changes in curriculum and teaching style. Students who are academically adaptable tend to be more engaged, have better problem-solving skills, and have better academic outcomes.
- **Psychological and social adaptability:** Psychological and social adaptability is the student's capacity to adjust his/her emotional and social life to an educational environment. This involves handling stress, developing self-confidence, developing positive relationships with teachers and peers, and being active learners. Good adaptability helps to enhance communication, emotional state, collaborative work, and study results [13]. It also helps in the student's engagement, social integration, and adaptation to new learning environments and technologies within modern inclusive classrooms.
- **Adaptability in online learning environments:** Adaptability in online learning settings is the ability of a student to adjust to the online settings, virtual classroom, and technology-driven learning approach [14]. Students who are adaptable will be able to effectively utilize online tools, stay engaged, maximize learning and enhance satisfaction in online learning.

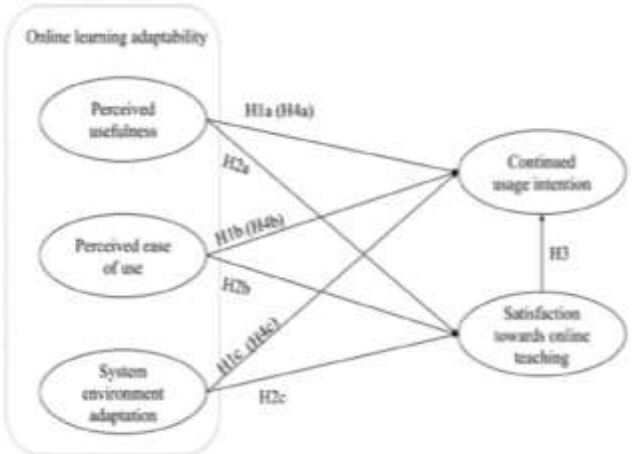

Fig. 2. Online learning adaptability factors

As shown in Fig. 1, the use of online learning platforms is positively affected by student satisfaction with the materials and their adaptability. The model emphasizes the perceived usefulness, perceived ease of use, and system environment adaptation as factors influencing student interaction, teacher satisfaction with the system and even their desire to return to the online learning platforms.

A. Types of Student Adaptability

Students can be classified into different types depending on how they cognitively, behaviourally, emotionally and socially react to an evolving education environment.

- **Cognitive adaptability:** A cognitive adaptable student is one who is able to change his or her thinking and learning approaches to fit different learning scenarios. This ability will help students working in new learning contexts understand complicated ideas such as [15] and adjust to changes in teaching approaches or educational technologies.
- **Behavioral adaptability:** Behavioral adaptability involves changing attitudes, actions and interactions in various educational environments [16]. Good behavior flexibility enhances classroom involvement, interaction with peers, socialization, communication with teachers and effectiveness of learning.
- **Emotional adaptability:** A student's ability to control their emotions, deal with academic stress and remain motivated despite challenging learning environments. This skill enables students to maintain a positive attitude, withstand stress and adapt to changes in their learning environment.
- **Social adaptability:** Social adaptability is defined as the student's ability to interact and work with teachers, peers and learning community in a range of educational settings. This ability helps develop excellent communication, teamwork and an ability to function in various social and cultural environments.

B. Factors Affecting Student Adaptability

Adaptability among students relies on academic, technological, social and psychological factors which affect the students' ability to adapt to new learning contexts, to use new technologies and to handle academic challenges.

1) Learning Environment

Learners' adaptability, engagement, participation and performance in the learning environment is strongly affected. Supportive and flexible classrooms promote communication, collaboration and active learning, and effective teacher guidance and adaptive resources enhance the overall learning process.

2) Internet Accessibility

Internet accessibility is essential for students to be successful in online and digital learning. A secure connection allows them to participate in the classes, utilize the resources and fully immerse themselves in their studies. A weak connection can also present issues that can interfere with learning and negatively impact academic achievement.

- Students' digital learning is directly influenced by having reliable internet.
- The poor internet connection poses difficulty in taking online classes, accessing learning resources and completing homework.
- In rural areas or from a low socioeconomic background, students often face connectivity problems which significantly impact learning continuity.
- Digital materials that can be accessed and internet speed that can be accessed enhances access and learning environment.

3) Family and Socioeconomic Conditions

Familiarity with the socio-economic and family background of students also has an impact on the adaptability and school performance of the students [17]. Well-off students are more likely to be able to access the resources of schools, to be able to access the internet and have parents' support, which makes them more motivated and have positive learning behavior. However, economic insecurity and scarce resources can have adverse impacts on adaptability, learning, and emotional health.

4) Motivation and Engagement

Motivated students are more likely to adapt successfully to new educational systems and learning technologies [18]. Active participation in discussions, assignments, and collaborative activities improves learning confidence and academic persistence, while low motivation can reduce participation, performance, and adaptability to changing educational environments.

5) Mental Health and Stress

Mental health strongly affects student adaptability and learning effectiveness. Academic pressure, stress, workload, and social isolation can negatively impact concentration, decision-making, and learning behavior. Emotional support, counseling services, stress-management strategies, and healthy learning environments help improve psychological well-being and adaptability [19].

6) Digital Literacy

Digital literacy refers to a student's ability to effectively use digital technologies, online platforms, and educational software for learning purposes. Students with strong digital skills can easily navigate virtual classrooms, online assessments, and e-learning resources [20].

C. Online Learning Adaptability

Online learning adaptability refers to a student's ability to effectively adjust to digital learning environments, virtual classrooms, and technology-based educational systems. It involves managing online learning challenges, maintaining engagement [14], using digital resources efficiently, and adapting to evolving instructional methods and remote learning activities.

D. Educational Data Mining and Learning Analytics

EDM and Learning Analytics (LA) are important approaches used to improve student adaptability and learning outcomes in modern educational systems [21][22]. These technologies use educational data, machine learning, and analytical techniques to identify learning patterns, predict student performance, and support personalized learning environments. Additionally, they assist teachers in keeping an eye on student participation, identifying at-risk students, and offering prompt academic assistance.

1) Educational Data Mining (EDM)

EDM applies data mining and ML techniques to analyze educational data such as student grades, attendance, assessments, and learning activities [23]. EDM aims to uncover meaningful patterns and predict student performance to optimize teaching and learning, and it supports four core types of applications in digital learning environments.

2) Learning Analytics (LA)

LA is the data-driven research method, whose core function is to collect, analyze, and interpret learner-related data to understand and optimize learning processes [24]. Its data sources cover educational interaction data such as those from learning management systems and student surveys. It can assess student behavior and support educational decision-making, with its core goal being to improve learning effectiveness through approaches such as personalized feedback [25]. It differs from educational data mining, which focuses on extracting potential patterns in datasets, and places greater emphasis on optimizing learning experiences through real-time feedback.

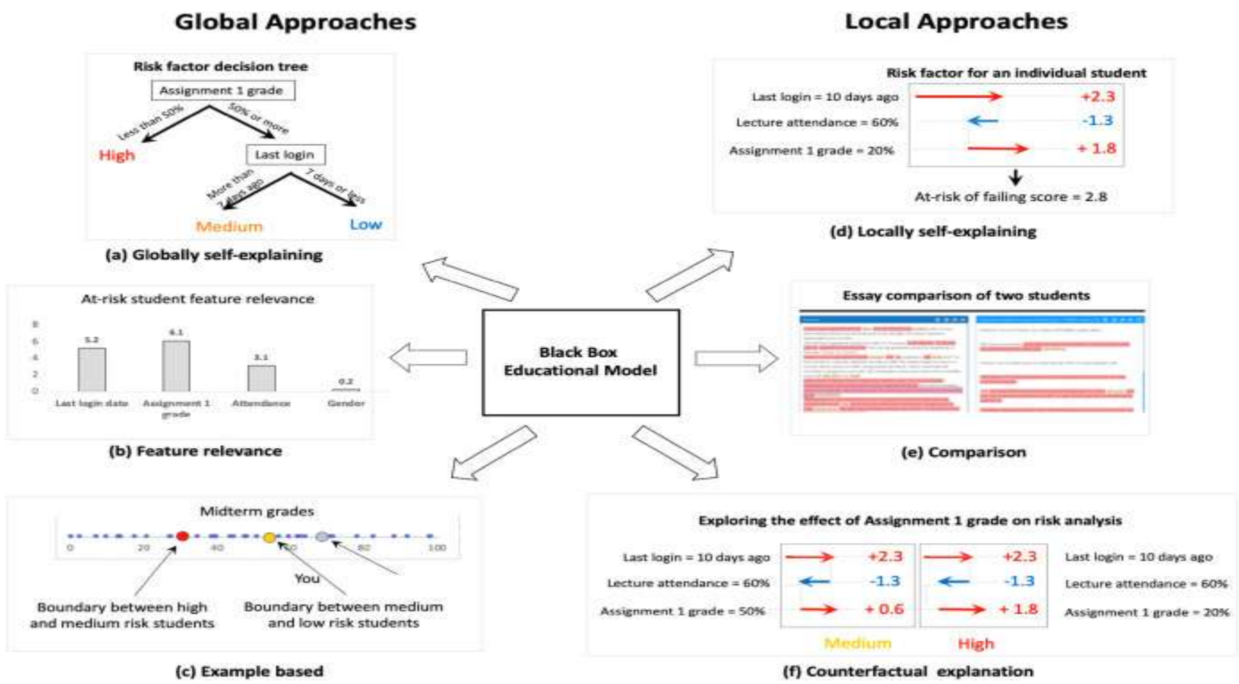

Fig. 3. Black-Box Education Model 3 Common explainability approaches

Fig. 2 illustrates common explainability approaches used to improve transparency in black-box educational models through global, local, feature-based, comparison, and counterfactual explanations

Interpretable Machine Learning (IML) focuses on developing machine learning models whose predictions and decision-making processes can be easily understood by humans, improving transparency, trust, accountability, and reliability in educational prediction systems [26].

E. Explainable AI (XAI) in Education

XAI in education focuses on making ML models transparent, understandable, and trustworthy for educators, students, and institutions. XAI helps explain how AI systems make predictions related to student performance, learning behavior, and adaptability. In educational data mining, XAI supports personalized learning, intelligent tutoring systems, and online learning environments by providing interpretable insights for decision-making. Frameworks such as ED-XAI highlight important factors, including stakeholders, benefits, model transparency, and ethical concerns [27]. XAI also improves trust in AI-driven educational systems by offering clear explanations, timely feedback, and understandable learning analytics for both teachers and students. There are some differences between interpretable IML and XAI illustrate in Table I below:

TABLE I. INTERPRETABLE MACHINE LEARNING AND EXPLAINABLE AI

Aspect	Interpretable Machine Learning (IML)	Explainable Artificial Intelligence (XAI)
Definition	Models that are naturally understandable	Techniques used to explain complex AI models
Model Type	Transparent and simple models	Black-box and complex models
Explainability	Built directly into the model	Generated using external methods
Examples	Decision Tree, Linear Regression	SHAP, LIME, Grad-CAM
Main Purpose	Human understanding and transparency	Trust and explanation of AI decisions
Complexity	Suitable for simpler tasks	Suitable for highly complex systems

Global explanations tell us about overall behavior and decision-making process of an ML model over all its training data. They aid researchers and educators in knowing the general functioning of the model and which features of the model are most important. Local explanations, on the other hand, explain a single prediction by the model on an individual basis, for a particular student or data instance. Local Interpretability can identify factors influencing a single prediction and can facilitate personalized education analysis.

F. Post-hoc Explainability

This involves post-facto methods of explainability after the machine learning model has finished making its prediction. These methods are mainly used for complex black-box models such as deep learning and ensemble systems [28]. Post-hoc methods assist users in gaining insights into the results of the prediction without altering the structure of the original model, thereby enhancing the transparency, trust, and interpretability of AI-driven educational systems

G. Explainability Techniques Used in Educational Systems

Multiple explainability approaches have been applied in the education field to enhance the transparency and reliability of adaptability prediction models for students. SHAP and LIME can be helpful in interpreting the results of the prediction and understanding how the features (e.g., attendance, learning behavior, assessment performance) affect the prediction. Attention mechanisms capture salient learning segments in educational data and feature-importance methods can serve to extract important features that influence students' adaptability [29]. Other ways of doing things to improve the results or outcomes when students' behaviors or learning activities are changed. Rule-based explanations provide a set of human-readable rules, which can be understood by educators, so that they can know what AI predictions are. These techniques enhance the trust, interpretability, fairness and decision of the student adaptability prediction system.

IV. LITERATURE REVIEW

The literature review gives an insight into the growing use of interpretable ML techniques in education on student performance prediction, student drop-out and learning styles and adaptability. The incorporation of explainable AI techniques, such as SHAP, to improve transparency, personalized learning assistance, and decision-making processes in adaptive educational settings is highlighted in recent studies.

I. K. Nti and S. Ramanayake (2026) develop an explainable AI (XAI) framework for predicting student dropout and supporting personalized educational interventions. RF and XGBoost models were trained using demographic, learning behaviour, and preference data, while SHAP provided global and instance-level interpretability. The models achieved strong performance across courses, with higher accuracy in Data Science than Web Development. Learning-style features showed limited impact on dropout prediction, supporting previous findings, while the study highlights that the models identify relationships rather than causal effects [30].

E. D. La Hoz, C. E. G. Yerena, and Ingrid Selene Torres-Rojas, (2026) suggests a ML architecture that may be explained to forecast undergraduate students' success on Colombia's SABER PRO test. Student background variables and standardized test scores were used to formulate a binary classification problem distinguishing desirable and undesirable outcomes. XGBoost, GLMNET, SVM, DT, and LDA were among the ML models evaluated using 10-fold cross-validation. The confusion matrix and area under the curve score were used to evaluate the performance of the model. SHAP-based explainability can provide both feature importance and local explanations for student performance, making it easy to identify the factors affecting students' performance [31].

M. Husayn, O. R. Adegboye, and A. Alzubi (2025) Reliable and comprehensible predictions of students' academic performance enable prompt interventions, tailored teaching, and effective utilization of resources. This paper proposes an ensemble design that optimizes the contributions of Random Forest, Extra Trees, and CatBoost models in order to boost prediction accuracy and transparency. The architecture would be directed by the GWO. A real-world student data set is used to test the framework, and its R^2 value of 0.93 is determined to be greater than that of the traditional ensemble approaches. SHAP-based interpretability identifies daily study hours, study effectiveness, lifestyle score, and screen time as the key variables influencing test success [32].

A. . F. Khan and S. R. A. Samad (2024). The period of pervasive deployment of Learning Management Systems (LMSs) and the transition to remote learning in the current COVID-19 environment has made student adaptation in online education a critical factor. This study proposes the Online Learner Adaptation Assessment using ML Techniques (OLAMLTs) framework to examine factors influencing adaptation by analyzing student involvement, performance data, and behavior. The framework identifies patterns of adaptation and offers customized educational recommendations by capturing elements such as self-regulation, motivation, and technical proficiency. The study seeks to improve the effectiveness, resilience and targeted educational interventions of online learning for the future [24].

S. G. Essa, T. Celik, and N. E. Human-Hendricks (2023). Current methods automatically tie students' behavioral features to certain learning styles (LSs) to improve the learning process through the application of ML algorithms, making e-learning more personalized. A comprehensive literature study covering the years 2015–2022, focused on LS models and ML techniques used in adaptive learning platforms, was conducted to identify patterns and knowledge gaps in this area. The study reviews current developments in applying ML to create intelligent e-learning environments that automatically detect learners' LSs and enhance learning. It also examines research platforms, LS models, evaluation methods, and learning support mechanisms [33].

D. Goštautaitė and L. Sakalauskas (2022) have demonstrated that a combination of ML algorithms and cognitive-behavioral approaches could automatically predict a learner's preferences for the various learning items and activities provided in an adaptive learning environment. Based on the previous e-learning activities, students' learning styles can be classified by generative and discriminative machine learning techniques. This research will concentrate on discriminative models, which will be used to determine the student behaviors associated with each student's preferred learning style. Additionally, a number of interpretability strategies that can be useful for multi-label models trained on partly and non-correlated data are examined in this study [34].

Table II summarizes recent studies on interpretable machine learning for student adaptability and performance prediction in educational systems, highlighting predictive accuracy, explainability techniques, adaptive learning applications, major challenges, and future research directions

TABLE II. A SUMMARY OF THE STUDY ON INTERPRETABLE USING ML FOR STUDENT ADAPTABILITY PREDICTION IN EDUCATIONAL SYSTEMS

Reference	Focus Area	Key Findings	Challenges	Key Contribution	Limitation and Future Work
I. K. Nti and S. Ramanayake (2026)	Explainable AI for student dropout prediction	Random Forest and XGBoost achieved strong predictive performance with SHAP-based interpretability	Learning-style attributes showed limited predictive influence	Integrated global and local explainability for dropout prediction	Limited causal interpretation and reduced generalizability across diverse educational domains
E. D. La Hoz, C. E. G. Yerena, and Ingrid Selene Torres-Rojas (2026)	Explainable ML for academic performance prediction	XGBoost and other ML models effectively predicted SABER PRO outcomes using SHAP explanations	Dependence on demographic and examination-based variables	Transparent identification of factors influencing academic success	Future studies should include behavioral and adaptability-related learning factors
M. Husayn, O. R. Adegboye, and A. Alzubi (2025)	Ensemble learning for student performance analysis	GWO-guided ensemble achieved high prediction accuracy ($R^2 = 0.93$)	Balancing model complexity with interpretability	Combined optimization and SHAP interpretability in educational prediction	Requires validation on larger and more diverse student datasets
A. . F. Khan and S. R. A. Samad (2024)	Student adaptability assessment in online learning	OLAMLT's framework identified adaptability patterns from engagement and behavioral data	Variability in learner behavior during remote learning	Introduced ML-based adaptability assessment for personalized interventions	Limited exploration of interpretable and transparent ML mechanisms
S. G. Essa, T. Celik, and N. E. Human-Hendricks (2023)	ML-based adaptive e-learning and learning styles	ML techniques improved automatic learning-style detection in adaptive platforms	Lack of unified evaluation standards for learning-style models	Systematic review of ML-driven adaptive learning environments	More research is needed on explainable and fairness-aware adaptive systems
D. Goštautaitė and L. Sakalauskas (2022)	Interpretable ML for learning-style prediction	Discriminative models effectively classified learner preferences from activity data	Multi-label learning and partially correlated data increase complexity	Investigated interpretability methods for adaptive learning models	Future work should address scalability and real-time interpretability in educational systems

V. CONCLUSION AND FUTURE WORK

The rising use of smart educational technologies has led to the growing significance of interpretable ML approaches in enhancing adaptability prediction and personalized learning support in educational systems. The studies reviewed show that ML models like DTs, RF, XGBoost, SVM, and deep learning methods can produce good predictive accuracy when analyzing learners' behaviors, learning progress, engagement, and online learning activities. Ensemble and DL models showed better prediction accuracy among the reviewed methods, and among interpretable methods, the SHAP, LIME, feature importance analysis, and rule-based explanations enhanced the transparency and trustworthiness of models. The results also indicate that learning behaviors, study patterns, motivation, attendance, digital literacy, and the use of the internet have a significant impact on the adaptability of the students and their learning results. Moreover, the use of explainable AI methods helps the teacher grasp the results of predictions so they can intervene early, adapt their teaching method and make decisions based on predictive data. In sum, the adoption of explainable AI and educational analytics creates more transparent, ethical, student-centred and intelligent learning environments.

Future studies should aim at creating scalable, fair, interpretable, machine learning models for real-time prediction of student adaptability. In order to enhance the transparency, personalization, and trustworthy decision-making in adaptive educational environments, further research into multimodal educational analytics, causal explainability, privacy-preserving learning, and human-centered AI systems is required.

REFERENCES

[1] Portia and R. Gupta, "Digital Evolution in Education," *Int. Res. J. Adv. Eng. Manag.*, vol. 2, no. 09, pp. 2911–2917, Sep. 2024, doi: 10.47392/IRJAEM.2024.0429.

[2] H. Sharma, S. Agarwal, M. Goel, and R. Sharma, "Revolutionizing Learning: The Impact of Digital Transformation on Education Systems," in *2025 5th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU)*, Dehradun, India: IEEE, 2025, pp. 1–6, November. doi: 10.1109/IOT-SIU65919.2025.11402748.

[3] K. Stockinger, R. Rinas, and M. Daumiller, "Student adaptability, emotions, and achievement: Navigating new academic terrains in a global crisis," *Learn. Individ. Differ.*, vol. 90, p. 102046, Aug. 2021, doi: 10.1016/j.lindif.2021.102046.

[4] R. Lingam, "AI-Powered Framework for Evaluating Child-Friendly Mobile Applications," *Int. J. Hum. Comput. Intell.*, vol. 4, no. 4, pp. 535–549, 2025, doi: 10.5281/zenodo.15624307.

[5] A. Malik *et al.*, "Forecasting students' adaptability in online entrepreneurship education using modified ensemble machine learning model," *Array*, vol. 19, p. 100303, Sep. 2023, doi: 10.1016/j.array.2023.100303.

[6] V. Rajendran, D. Besiahgari, S. C. Patil, V. Challagulla, and M. Chandrashekaraiah, "Academic Temporal Pattern Mining for Enhanced Student Performance Prediction: A Hybrid Machine Learning Approach," in *2025 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI)*, IEEE, Mar. 2025, pp. 1–6. doi: 10.1109/ICDSAAI65575.2025.11011532.

[7] E. Elbasi, M. Nadeem, Y. I. Alzoubi, A. E. Topcu, and G. Varghese, "Machine Learning in Education: Innovations, Impacts, and Ethical Considerations," *IEEE Access*, vol. 13, pp. 128741–128770, 2025, doi: 10.1109/ACCESS.2025.3590134.

[8] R. Rao Thallada, N. Alapati, and K. Nallabothu, "Explainable AI-Driven Predictive Risk Management Framework for Enterprise GRC Platforms," Apr. 09, 2026. doi: 10.21203/rs.3.rs-9328473/v1.

[9] L. Liu and L. Wan, "Innovative models for enhanced student adaptability and performance in educational environments," *PLoS One*, vol. 19, no. 9, p. e0307221, Sep. 2024, doi: 10.1371/journal.pone.0307221.

[10] G. T. Yamamoto and F. Karaman, "Education 2.0," *Horiz.*, vol. 19, no. 2, pp. 109–117, May 2011, doi: 10.1108/10748121111138308.

[11] E. Tikhonova and L. Raitskaya, "Education 4.0: The Concept, Skills, and Research," *J. Lang. Educ.*, vol. 9, no. 1, pp. 5–11, Mar. 2023, doi: 10.17323/jle. 2023.17001.

[12] A. N. Pathak, "Exploring the Relationship Between Learning Adaptability and Academic Achievement," *Glob. J. Progress. Educ. A Ref. Res. J.*, vol. 12, no. 2, pp. 149–153, 2022, doi: 10.46360/globus.edu.220222027.

[13] S. Karabalaev, G. Karabalaeva, J. Niyazova, S. Nurbekova, and D. Aytimbetova, "Research on the socio-psychological adaptation of students with disabilities in higher education institutions," *Ric. Di Psicol.*, vol. 48, no. 2, pp. 57–88, Feb. 2026, doi: 10.3280/rip2025oa21843.

[14] Z. Li *et al.*, "Students' online learning adaptability and their continuous usage intention across different disciplines," *Humanit. Soc. Sci. Commun.*, vol. 10, no. 1, p. 838, Nov. 2023, doi: 10.1057/s41599-023-02376-5.

[15] I. Purbasari, M. Yusuf, Subagya, S. Marmoah, and A. A. Alali, "Development of a community-based social collaborative e-learning model for adaptability of higher education students in Indonesia," *Front. Educ.*, vol. 10, Apr. 2025, doi: 10.3389/feduc. 2025.1487484.

[16] D. W. Putwain, K. Loderer, D. Gallard, and J. Beaumont, "School-related subjective well-being promotes subsequent adaptability, achievement, and positive behavioral conduct," *Br. J. Educ. Psychol.*, vol. 90, no. 1, pp. 92–108, Mar. 2020, doi: 10.1111/bjep. 12266.

[17] A. Chen, "Relationship between Family Socioeconomic Status and Online Education Usage: a Data Analysis Based on K-12 Students," *J. Educ. Res. Pract.*, vol. 2, no. 3, pp. 339–350, Nov. 2024, doi: 10.70376/jerp.v2i3.205.

[18] L. Wu and J. M. W. Gopez, "A Review of Academic Motivation and Student Engagement in Blended Learning within the Chinese Educational Context," *Int. J. Multidiscip. Res.*, vol. 6, no. 5, pp. 1–8, 2024.

[19] Iqra, "A systematic – Review of academic stress intended to improve the educational journey of learners," *Methods Psychol.*, vol. 11, p. 100163, Dec. 2024, doi: 10.1016/j.metip.2024.100163.

[20] R. Radicuks, I. Bula-Biteniece, B. Boobani, and S. Vilks, "Digital literacy in school education: A qualitative systematic review," *Multidiscip. Rev.*, vol. 9, no. 1, pp. 1–11, July, 2025.

[21] M. S. Khine, "Educational Data Mining and Learning Analytics," in *Artificial Intelligence in Education*, Singapore: Springer Nature Singapore, 2024, pp. 1–159. doi: 10.1007/978-981-97-9350-1_1.

[22] C. Romero and S. Ventura, "Educational data mining and learning analytics: An updated survey," *WIREs Data Min. Knowl. Discov.*, vol. 10, no. 3, p. e1355, May 2020, doi: 10.1002/widm. 1355.

[23] A. Rabelo, M. W. Rodrigues, C. Nobre, S. Isotani, and L. Zárate, "Educational data mining and learning analytics: a review of educational management in e-learning," *Inf. Discov. Deliv.*, vol. 52, no. 2, pp. 149–163, Mar. 2024, doi: 10.1108/IDD-10-2022-0099.

[24] A. . Feroz Khan and S. R. A. Samad, "Evaluating Online Learning Adaptability in Students Using Machine Learning-Based Techniques: A Novel Analytical Approach," *Educ. Sci. Manag.*, vol. 2, no. 1, pp. 25–34, Mar. 2024, doi: 10.56578/esm020103.

[25] K. Dixit, "Predictive Analytics in Business Intelligence for Sales Forecasting," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 60, no. 3, p. 981, Sep. 2023, doi: 10.48175/IJARSCT-12750G.

[26] K. Topuz, A. Bajaj, K. Coussement, and T. L. Urban, "Interpretable machine learning and explainable artificial intelligence," *Ann. Oper. Res.*, vol. 347, no. 2, pp. 775–782, April, 2025, doi: 10.1007/s10479-025-06577-w.

[27] D. Pantazatos, A. Trilivas, K. Meli, D. Kotsifakos, and C. Douligeris, "Machine Learning and Explainable Artificial Intelligence in Education and Training - Status and Trends," *Int. Wireless. Internet Conf.*, vol. 527, pp. 110–122, 2024, doi: 10.1007/978-3-031-58053-6_8.

[28] R. Meylani, "Explainability in Educational AI: A Critical Systematic Review," in *4th International Science, Education, Art & Technology Symposium*, 2025, pp. 403–415, October.

[29] S. Gunasekara and M. Saarela, "Explainable AI in Education: Techniques and Qualitative Assessment," *Appl. Sci.*, vol. 15, no. 3, p. 1239, Jan. 2025, doi: 10.3390/app15031239.

[30] I. K. Nti and S. Ramanayake, "Explainable machine learning for student dropout prediction and tailored interventions in online personalized education," *Discov. Artif. Intell.*, vol. 6, no. 1, p. 288, Feb. 2026, doi: 10.1007/s44163-026-01016-6.

[31] E. De La Hoz, C. Garcia-Yerena, and I. Torres-Rojas, "Actionable Learning Analytics: Predicting University Performance Levels with Interpretable Machine Learning," *J. Effic. Responsibility. Educ. Sci.*, vol. 19, no. 1, pp. 15–27, Mar. 2026, doi: 10.7160/eriesj. 2026.190102.

[32] M. Husayn, O. R. Adegboye, and A. Alzubi, "GWO-Optimized Ensemble Learning for Interpretable and Accurate Prediction of Student Academic Performance in Smart Learning Environments," *Appl. Sci.*, vol. 15, no. 22, p. 12163, Nov. 2025, doi: 10.3390/app152212163.

[33] S. G. Essa, T. Celik, and N. E. Human-Hendricks, "Personalized adaptive learning technologies based on machine learning techniques to identify learning styles: A systematic literature review," *IEEE Access*, vol. 11, pp. 48392–48409, 2023.

[34] D. Goštautaitė and L. Sakalauskas, "Multi-Label Classification and Explanation Methods for Students' Learning Style Prediction and Interpretation," *Appl. Sci.*, vol. 12, no. 11, pp. 1–19, May, 2022, doi: 10.3390/app12115396.

