

Learning Analytics and Educational Data Mining: Transforming Student Success in Higher Education

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Abstract

Digital learning environments have experienced exponential growth, resulting in an unprecedented amount of educational data that can be used to transform student success in higher education. This comprehensive review discusses the convergence of Learning Analytics (LA) and Educational Data Mining (EDM) as complementary techniques to understanding, predicting and improving student learning outcomes. In Higher Education, data analytics offers a particular promise in the domains of analysis, understanding and modelling of pedagogical processes, and methodologies can lead to the emergence of highly correlative terms like Learning Analytics, Academic Analytics and Educational Data Mining, where the result of one can feed into the next. This review aims to provide a synthesis of evidence on the applications, techniques, theory and empirical effects of these data-driven approaches by systematically analysing peer-reviewed literature published from 2020 to 2025. The key findings include that early warning systems, predictive analytics, and personalized learning interventions can have a significant impact on student retention, engagement, and achievement. Research shows that students who were exposed to AI-based adaptive feedback made a 28% increase in conceptual understanding, whereas the control group made a 14% increase; student engagement rose by 35%, and cognitive overload decreased by 22%. Nevertheless, there are significant challenges, such as digital divides, especially in developing nations, algorithmic bias, data privacy considerations and ethical governance. The review suggests an integrated LA-EDM approach to improving student success and pinpoints methodological, geographic and policy gaps that need further research. The synthesis offers practical guidance to educators, administrators, policymakers, and researchers looking to leverage data-driven practices without compromising ethical considerations and equity in education.

Keywords: Learning Analytics, Educational Data Mining, Student Success, Higher Education, Predictive Analytics, Personalized Learning, Artificial Intelligence in Education

1. Introduction

1.1 Background

The digital revolution has changed the face of higher education, creating massive amounts of data with the potential to gain insights into and improve student success. Institutions of higher learning are currently undergoing significant transformation within the education and operations landscape, such as digital transformation, online courses, digital-native students, cost reduction

and micro and nano degrees. With the development of sophisticated analytical tools and methodologies, institutions have shifted their decision-making from intuition to evidence-based and data-driven approaches, which are leveraging the power of data to drive education.

1.2 Global Expansion of Educational Data

In today's context, with the growing number of Learning Management Systems (LMS), web-based learning environments, and online learning materials, the opportunities for data collection and analysis in educational settings are unprecedented. The convenience and embeddedness of data collection in educational technologies, combined with the computational techniques, have pushed the analysis of big data from proof-of-concept demonstrations to the use of techniques in various educational fields. This data revolution involves a variety of data sources, such as student information systems, LMS interaction logs, assessment records and increasingly more sophisticated sensors that collect multimodal learning data (Luan et al., 2020).

The use of multimodal learning analytics has gained popularity in the field of learning analytics, and can be used to gain an accurate representation of the learning processes by categorizing the data into digital data, physical data, physiological data, psychometric data and environment data; and learning indicators such as behavior, cognition, emotion, collaboration, and engagement. (Mu et al., 2020)

1.3 Emergence of Learning Analytics

In the early 2010s, Learning Analytics came into its own as a new discipline, according to the Society for Learning Analytics Research (SoLAR), as "the measurement, collection, analysis and reporting of data about learners and their contexts for purposes of understanding and optimising learning and the environments in which it occurs. The aim of learning analytics is to provide an overview of the applications of data analytics in education, to propose common definitions and frameworks for education data analytics for decision making at the level of individual student, class, curriculum, school and educational system. (Nguyen et al., 2020)

The learning, analytics, and AI in education is a multi-dimensional perspective on the role of AI, highlighting the complex relationships between AI, analytics, and the learning process. This convergence has opened up new opportunities for comprehending learning on a scale while tailoring learning experiences for each student. (Cukurova, 2024)

1.4 Emergence of Educational Data Mining

One of the complementary approaches is Educational Data Mining (EDM), which is a kind of data mining technique used in an educational context. Educational data mining is a new scientific field concerned with the design and application of techniques to interpret data collected in education contexts, which has grown to encompass a range of techniques and data sources. From the traditional statistical methods, EDM techniques have progressed to more advanced machine learning algorithms that can detect intricate patterns within educational data (Papadogiannis et al., 2024).

1.5 Significance for Higher Education

A clear understanding of the importance of LA and EDM in higher education is crucial, especially in an era of rising accountability, budget pressures, and expectations for better student outcomes. Higher education institutions need to leverage data analytics tools such as educational data mining, learning analytics and business intelligence to derive knowledge and insights from educational data to enable institutional leadership to monitor and enhance student enrollment campaigns, track student performance, evaluate academic staff and make data driven decisions. (Gaftandzhieva et al., 2023)

With a complex and competitive environment, institutions of higher education need to rely on data-driven governance to improve decision-making processes, and the use of data analytics will enable better decision making and increase the effectiveness of the institutions. (Kasope et al., 2024)

1.6 Research Objectives

The purpose of this review is to: Integrate conceptual underpinnings and theory from which to base LA and EDM 2. Discuss the uses and methods used in the higher education setting 3. Identify the empirical evidence on impacts to student success indicators 4. Know the new technologies and trends in the field 5. Examine ethical, legal and privacy issues related to data in education 6. Outline a comprehensive plan for the implementation of LA-EDM 7. Identify gaps in research and future avenues of research

1.7 Research Questions

The following research questions are addressed in this review: RQ1: What are the conceptual foundations and distinguishing characteristics of LA and EDM? RQ2: How are LA and EDM techniques being applied to enhance student success in higher education? RQ3: What is the empirical evidence regarding the impact of LA and EDM on student outcomes? RQ4: What emerging technologies are shaping the future of data-driven education? RQ5: What ethical and privacy challenges must be addressed for responsible implementation? RQ6: What research gaps exist and what future directions should be prioritized?

2. Methodology

2.1 Review Design

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines are followed to ensure methodological rigor and transparency in this systematic literature review. A thorough search strategy is used to find relevant peer-reviewed literature in various databases related to learning analytics and educational data mining in higher education.

2.2 Search Strategy

A search strategy was used, which involved the use of Boolean operators to combine key terms across three conceptual areas: learning analytics OR educational data mining OR academic analytics; higher education OR university OR tertiary education; student success OR academic

performance OR retention OR engagement. The major academic databases were searched as detailed in Table 1.

2.3 Databases Searched

Table 1: Search Strategy and Databases

Database	Focus Area	Search Period
Scopus	Multidisciplinary	2020-2025
Web of Science	Multidisciplinary	2020-2025
IEEE Xplore	Technology/Engineering	2020-2025
ACM Digital Library	Computing	2020-2025
ERIC	Education	2020-2025
Google Scholar	Multidisciplinary	2020-2025
SpringerLink	Multidisciplinary	2020-2025
ScienceDirect	Multidisciplinary	2020-2025

2.4 Inclusion Criteria

Studies were excluded if they: - were not published in peer-reviewed journals or conference proceedings - did not focus on learning analytics or educational data mining in higher education - were not published between 2020 and 2025 - were not written in English - did not report empirical findings, theoretical frameworks or systematic reviews - did not address student success indicators such as performance, retention, engagement or satisfaction

2.5 Exclusion Criteria

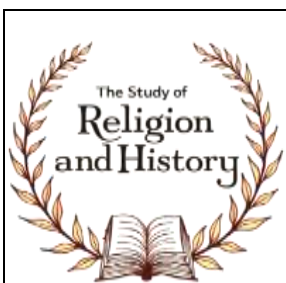
Studies were not included when they: - Only included K-12 or primary/secondary education - Were non-peer-reviewed publications (editorials, opinion pieces, white papers) - Did not directly address learning analytics or educational data mining - Were published prior to 2020 (unless foundational studies) - Were duplicates across databases

Table 2: Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Publication Type	Peer-reviewed articles, reviews	Editorials, opinion pieces
Date Range	2020-2025	Pre-2020 (except foundational)
Educational Level	Higher Education	K-12 only
Language	English	Non-English
Focus	LA/EDM applications	Unrelated topics
Quality	Indexed in major databases	Non-indexed sources

2.6 Screening Process

A preliminary search of the database resulted in 2,847 possible matches. 2235 records were screened for title and abstract after deletion of duplicates (n=612). Of these, 487 full-text articles

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were evaluated for eligibility and 70 studies were included in the final synthesis, which met all the criteria.

2.7 Data Extraction Procedure

Data extraction utilized a standardized data extraction template which included the following data: author(s), year, country, study design, sample characteristics, LA/EDM techniques used, outcome measures, key findings, and limitations. Appropriate tools were used for the quality assessment of each study design.



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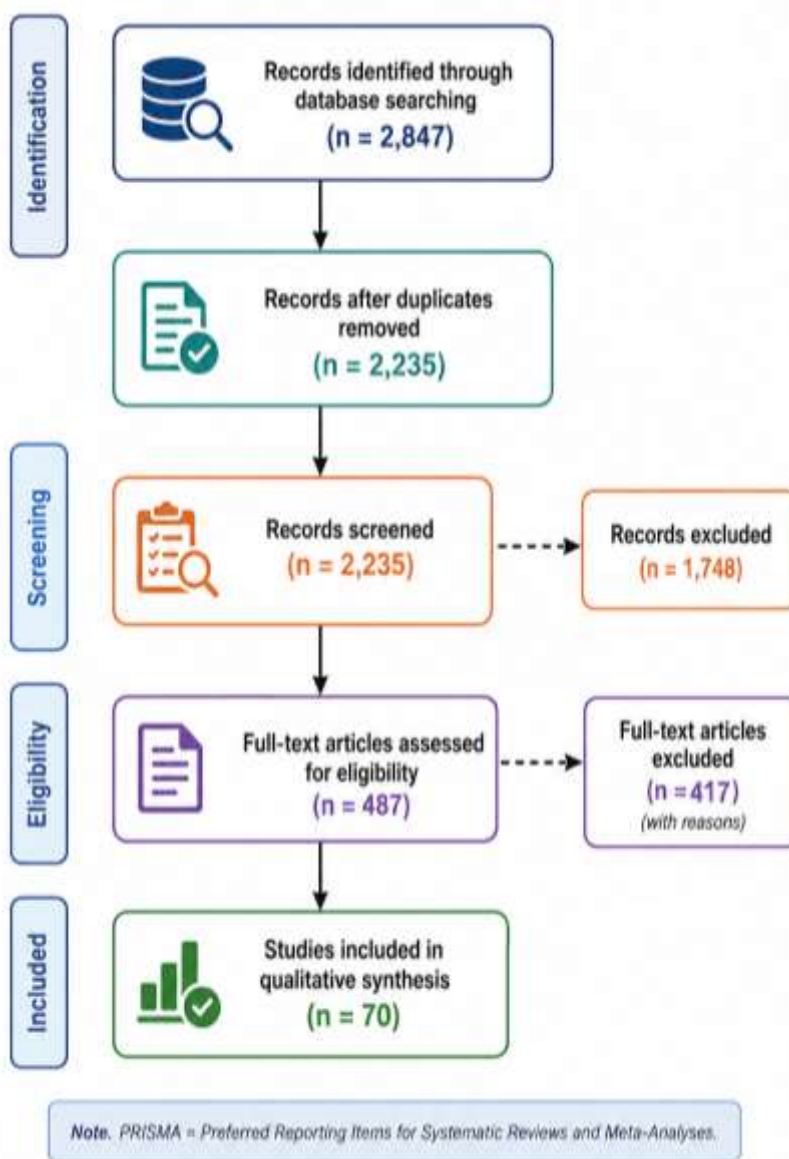


Figure 1: PRISMA Flow Diagram

3. Conceptual Foundations

3.1 Learning Analytics

3.1.1 Definitions

Learning Analytics is an interdisciplinary research area that combines education, data science, machine learning and human-computer interaction to gain insights into and enhance the learning process. Data analytics in HE offers specific possibilities to analyse, understand and model pedagogical processes and methodologies and processes which resulted in the creation of unique terms such as Learning Analytics, Academic Analytics and Educational Data Mining. (Nguyen et al., 2020)

The fast growth of Learning Analytics and Artificial Intelligence in Education provides scalable, data-driven systems, but also creates problems with data privacy and agency, such that the exclusion of the stakeholders involved in the design process could cause mistrust and result in the creation of poorly aligned systems. (Alfredo et al., 2024)

3.1.2 Evolution

The development of learning analytics has been through a number of stages. The field began with descriptive analytics reporting what had happened, but it has now grown to predictive and prescriptive analytics that predict what is likely to happen and suggest what action to take. Learning analytics dashboards give educators and students a whole picture of the learning domain, with visualizations showing students their learning behavioral patterns increasing their own awareness of their learning progress and helping educators identify students who might be struggling with learning. (Ramaswami et al., 2022)

3.1.3 Major Frameworks

Various models have been suggested to inform implementation and research on LA. A four-dimensional theoretical model for virtual reality-based teaching suggests structural components that could be used together with learning analytics prototype systems and results are anticipated to aid practitioners in making the best use of their interventions. (Christopoulos et al., 2020)

Educational Data Mining and Machine Learning algorithms could be applied to extract valuable information from a large amount of collected data from educational institutions to support decision making; Learning Analytics Intervention studies could be used to predict levels of risk for a student and to provide the relevant information to the relevant stakeholders to support targeted interventions. (Alalawi et al., 2025)

3.2 Educational Data Mining

3.2.1 Definitions

The purpose of Educational Data Mining is to use computational methods to analyze educational data to reveal patterns, make predictions and gain insights that will enhance educational outcomes. EDM is a new scientific field that aims at the development and application of techniques to analyze data that are produced in the educational environment, such as

classification, regression analysis, clustering, association rule mining and Natural Language Processing. (Papadogiannis et al., 2024)

3.2.2 Evolution

As time went on, the techniques employed and the kinds of data analyzed have become more sophisticated. In higher education, educational data mining methods are implemented for prediction of students' performance and improvement of learning outcomes, using machine learning algorithms to find a correlation between courses and the prediction of grades. (Angeioplastis et al., 2025)

3.2.3 Techniques

Some of the most popular core EDM techniques are classification, clustering, regression, association rule mining, and recently, deep learning methods. Random Forest, Decision Tree, Naive Bayes, Neural Network and K-Nearest Neighbours were some machine learning algorithms applied in the prediction of student academic performance; however, the evaluation metrics used in the different studies were different. (Khairy et al., 2024)

3.3 Relationship between Learning Analytics and Educational Data Mining

Although they share the same goals, there are differences between LA and EDM in terms of their primary orientations and focus on stakeholders. The outcome of one approach can then be the input in another approach, and researchers can find new contexts and new areas of inquiry when thinking through the data analytics components in an integrated way. (Nguyen et al., 2020)

Table 3: Comparison of Learning Analytics and Educational Data Mining

Dimension	Learning Analytics	Educational Data Mining
Primary Focus	Understanding and optimizing learning	Discovering patterns in educational data
Stakeholder Orientation	Learners, instructors, institutions	Researchers, system developers
Methodological Emphasis	Visualization, dashboards, interventions	Algorithmic development, model building
Data Sources	LMS logs, assessment data, surveys	Large-scale educational databases
Primary Outcomes	Real-time feedback, early warnings	Predictive models, knowledge discovery
Temporal Focus	Immediate to short-term	Historical analysis, long-term patterns
Human Involvement	High (interpretation, intervention)	Variable (automated to human-guided)

4. Theoretical Foundations

For LA and EDM to be effective, it is important that they are built on solid knowledge of learning theories that account for how learners acquire knowledge, learn skills and control their learning processes.

4.1 Self-Regulated Learning Theory

The theory of self-regulated learning (SRL) is important for understanding how students monitor and control their learning processes. Different uses of learning analytics can be explored to understand how LA can be used to provide an indication of a learner's current self-regulation state and support the different phases of the SRL cycle. (Heikkinen et al., 2022)

Self-Regulated Learning is correlated with higher learning performance, and when the students do not regulate their learning spontaneously, scaffolding in their learning using SRL strategies in computer-based learning environment can be done to improve the learning outcomes. (Lim et al., 2022)

4.2 Constructivism

The teaching theory of constructivist is based on the idea that learners construct their knowledge by interacting with their surroundings and reflecting on experiences. Research on higher education students' online instruction perceptions indicates that cognitivism, connectivism, and constructivism were the most used theories of online instruction, with motivation and satisfaction mostly positively perceived by students. (Tan et al., 2021)

4.3 Connectivism

Connectivism – a learning theory for the digital age – focuses on the process of connecting specialised nodes or information. Theories such as behaviorism, constructivism, cognitivism, situated learning, problem-based learning, context awareness learning, socio-cultural theory, collaborative learning, conversational learning, lifelong learning, informal learning, activity theory and connectivism are employed to support and guide mobile learning implementation. (Naveed et al., 2023)

4.4 Learning Sciences

The learning sciences offer empirical support to understanding the cognitive processes, motivation, and social aspects of learning. The narrow perspective of AI in education as tools is challenged by the need for alternative conceptions of AI to enable human-AI hybrid intelligence, as in early learning sciences, AI in Education Research has moved away from the analogy of AI to human intelligence. (Cukurova, 2024)

4.5 Data-Driven Decision-Making Theory

Data-driven decision-making theory offers a set of frameworks for the successful use of data for informing practice and policy in education. HEIs need to leverage on data analytics tools such as educational data mining, learning analytics and business intelligence to leverage insights and knowledge from educational data and to monitor and enhance student enrollment campaigns,

track student performance, assess academic staff and make data-driven decisions. (Gaftandzhieva et al., 2023)

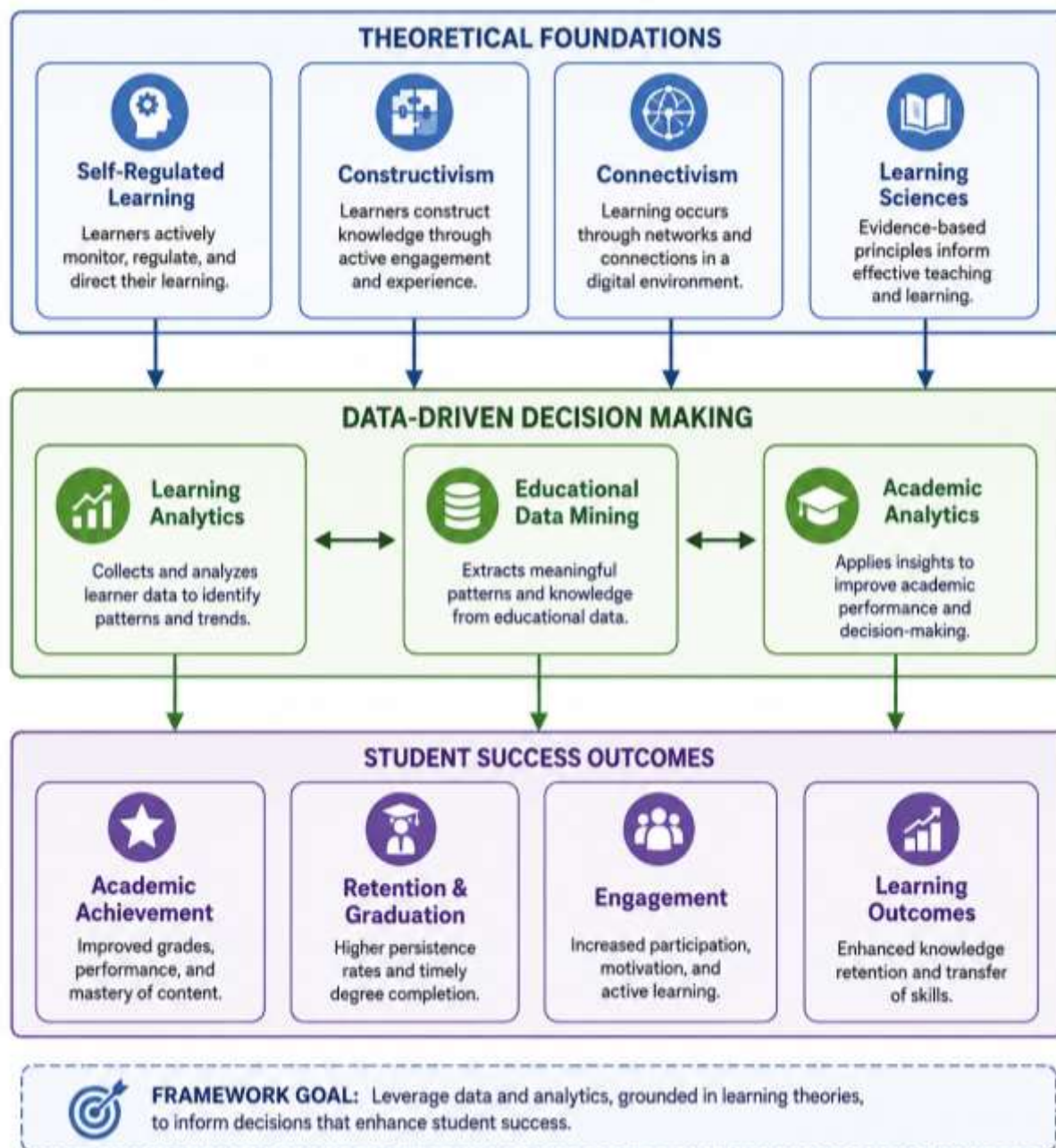


Figure 2: Theoretical Framework Linking Analytics to Student Success

5. Learning Analytics Applications in Higher Education

5.1 Early Warning Systems

One of the most promising uses of learning analytics is early warning systems that can be used by institutions to detect students at risk of dropping out or disengaging before they do. The ability to predict university student graduation is a useful tool for both students and institutions, as it can help students make informed choices about their academic and career plans, and also help institutions identify students who may be at risk of failing and provide them with additional support to achieve success. (Pelima et al., 2024)

Learning Analytics Intervention studies involve using learning analytics tools to predict students' risk levels and share them with relevant stakeholders for targeted interventions, such as academics, administrators, and students, and have demonstrated success in enhancing outcomes such as pass rates, retention, and grades. (Alalawi et al., 2025)

5.2 Student Retention and Persistence

Student retention is a key issue for higher education institutions, and LA offers strong insights and strategies for understanding and mitigating the factors that impact student retention. The study found that when students interact with AI-generated feedback frequently, there is a 40% higher retention rate, indicating the promise of AI-powered smart learning environments to improve educational equity. (Naseer & Khawaja, 2025)

5.3 Academic Performance Prediction

Forecasting academic success provides the opportunity to intervene early and provide individual assistance to students who are having difficulty. The prediction of university student graduation using machine learning has been the focus of interest, and large scale datasets of student academic data have been used to train machine learning algorithms that detect patterns which can be used to make predictions in a new data set with accuracy as high as 90%. (Pelima et al., 2024)

In an attempt to predict the overall performance of students in higher education institutions, a study was conducted on 772 students where the Random Forest model had an accuracy of 88.3% in predicting successful students using video learning analytics and data mining techniques. (Hasan et al., 2020)

5.4 Personalized Learning

In the context of personalized learning, LA is used to customize learning experiences to the needs, preferences and abilities of each learner. Individual student characteristics and personalisation are identified as being key to successful learning experiences and the following factors are highlighted as key considerations for improved learning outcomes: learner profiling, content adaptation and responsive assessment approaches. (Castro et al., 2024)

Personalized e-learning system is able to deliver enhanced learning to its users by delivering learning contents and assessments based on AI based techniques which decide the suitable contents for the learner according to his level of understanding and the learning mode. (Murtaza et al., 2022)

5.5 Adaptive Learning Systems

Adaptive systems are learning systems that dynamically vary content, pacing and instructional strategies based on real-time assessment of student performance and engagement. In the context of personalized learning and adaptive assessment, AI has the potential to enhance students' performance, engagement, and motivation, but it is important to recognize potential limitations such as bias and discrimination. (Halkiopoulos & Gkintoni, 2024)

A reinforcement learning-based smart e-learning framework with Markov Decision Process has the potential to enhance the learning experience for each student by providing them with a personalized and effective learning path, with the MDP allowing for adjusting recommendations to find new activities and learning paths based on learners' feedback. (Amin, Uddin, Alarood, et al., 2023)

5.6 Student Engagement Monitoring

Student engagement monitoring gives information on student learning behaviors and allows the implementation of timely interventions. The strategies suggested for engaging students in blended learning are: using and combining the synchronous and asynchronous modes, clearly communicating course expectations and establishing trusting relationships, and various digital tools were suggested that can be used to engage students behaviorally and emotionally. (Heilporn et al., 2021)

The ability to identify, track, monitor, analyse and visualize multimodal learning data of students' behaviour, emotion, cognition and affect in real-time proved to be a major benefit which is vital towards the realisation of adaptive and personalized learning. (Lampropoulos & Evangelidis, 2025)

5.7 Curriculum Enhancement

Patterns of student progress, identification of difficult concepts, and effectiveness of instructional approaches can direct curriculum design and enhancement using learning analytics. The impact of digital technologies on education, skills and employment is huge and insights confirm the importance of investing in education for growth and development of high technology skills as education's future is digital. (Qureshi et al., 2021)

5.8 Institutional Decision-Making

Strategic planning, institutional resource allocation, and quality assurance processes are supported at the institutional level by LA. The framework underscores the need to gather, examine, and leverage data from multiple aspects of the institution's operations, such as academic achievement, student engagement, financial management, and operational efficiency, to inform trends, predictions, and strategies that support the institution's mission and goals. (Kasope et al., 2024)

Data-driven decision making and SDGs can contribute to the development of HEI efficacy, inclusion and job-readiness of graduates, and data analytics can help enhance HEI efficacy,

curriculum relevance, student outcomes and create an inclusive academic environment. (Chigbu & Makapela, 2025)

Table 4: Major Applications and Educational Benefits

Application	Primary Benefit	Key Stakeholders	Implementation Complexity
Early Warning Systems	Timely identification of at-risk students	Advisors, instructors, students	Moderate
Retention Analytics	Reduced attrition, improved completion rates	Administrators, advisors	Moderate-High
Performance Prediction	Targeted support, personalized interventions	Instructors, students	Moderate
Personalized Learning	Improved engagement, better outcomes	Students, instructors	High
Adaptive Systems	Dynamic content adjustment, optimal pacing	Students	High
Engagement Monitoring	Real-time feedback, early intervention	Instructors, administrators	Moderate
Curriculum Enhancement	Evidence-based course improvement	Curriculum designers, faculty	Moderate
Institutional Analytics	Strategic planning, resource optimization	Administrators, policymakers	High

6. Educational Data Mining Techniques

6.1 Classification

Classification techniques: They classify students or learning events into pre-determined categories using input features. Major machine learning algorithms like Random Forest, Decision Tree, Naive Bayes, Neural Network and K-Nearest Neighbors are used to predict student academic performance, among which Random Forest and Decision Tree classifiers are the best performing algorithms. (Khairy et al., 2024)

Based on the review, the most frequent technique used is the prediction of students' academic performance using data from the Learning Management System and Student Information System,

which are commonly used algorithms: Support Vector Machine and Random Forest. (Pelima et al., 2024)

6.2 Clustering

The clustering techniques classify students or learning behaviors into groups without any set criteria and show the natural patterns in the educational data. K-means clustering can be employed to get a categorised target variable for global school performance, while decision trees can be used to get predictive models revealing the influence of educational factors on performance in high-SES schools, and country-level socioeconomic indicators on performance in low-SES schools. (Gamazo & Abad, 2020)

6.3 Regression

Regression techniques make predictions for continuous outcome variables like grades or completion times. For providing personalized course recommendations, the machine learning algorithms used are Random Forest Regressor, Decision Tree Regressor, K-Nearest Neighbors, Singular Value Decomposition, eXtreme Gradient Boosting Regressor and Linear Regression, with Singular Value Decomposition having the best performance in terms of accuracy. (Amin, Uddin, Mashwani, et al., 2023)

6.4 Association Rule Mining

Association rule mining is used to find the relationship between variables in educational data. Association rule mining is the most popular technique in data mining research, which extracts potentially useful information and knowledge from large-scale data sets, and the Apriori algorithm is used to systematically analyze the patterns of data. (Zhao et al., 2021)

6.5 Neural Networks and Deep Learning

Deep learning methods have shown to have strong performance on high-dimensional and complicated educational data. The results revealed that the machine learning models such as ANN and Decision Trees were accurate and stable in predicting student outcomes, with the ANN having a higher accuracy rate but was not transparent, while using LIME and SHAP methods, the results showed high fidelity in the output predictions of the machine learning models. (Gunasekara & Saarela, 2025)

6.6 Natural Language Processing

NLP techniques can be used to analyze text data such as discussion posts, essays, and feedback. In the textual format, NLP techniques have been found to be very helpful in analyzing student feedback, and existing methods have been modified to use in the educational domain, such as sentiment annotations, entity annotations, summarization of text, and topic modeling. (Shaik et al., 2023)

In education, sentiment analysis is used to listen to students' opinions and improve learning-teaching practices pedagogically, and the improvements of sentiment annotation techniques and AI methodologies allow that students' comments can be annotated with their sentiment orientation with little human effort. (Shaik et al., 2022)

6.7 Predictive Analytics

Predictive analytics is a collection of several methods to predict student outcomes. The state-of-the-art dashboards include concepts of descriptive analytics components and leverage machine learning to support predictive and prescriptive analytics, with the use of emerging analytics tools, allowing learners to correctly interpret the behavior of the predictive models and understand the prediction process. (Sušnjak et al., 2022)

6.8 Recommendation Systems

Recommendation systems are used to recommend learning resources, courses or activities according to the student profile and behavior. In recent years, the relevance of recommendable education resources has been enhanced through collaborative, content and hybrid recommendation systems, and machine learning has been increasingly utilized to facilitate students' learning processes, which is a reaction to the challenges resulting from the information overload in the field of education. (Urdaneta-Ponte et al., 2021)

The issues occurring in the current personalized recommendation systems are that they are unaware of the content, students' discontinuity, language barriers, confusion in choosing study materials, insufficient infrastructure, and funding problems, and new digital technologies are proposed to solve these problems. (Dhananjaya et al., 2024)

Table 5: EDM Techniques, Purposes, Strengths, and Limitations

Technique	Purpose	Strengths	Limitations
Classification	Categorize students/outcomes	High accuracy, interpretable	Requires labeled data
Clustering	Discover natural groupings	Unsupervised, pattern discovery	Cluster interpretation challenging
Regression	Predict continuous outcomes	Quantitative predictions	Assumes linear relationships
Association Mining	Find variable relationships	Rule discovery	Computationally intensive
Neural Networks	Complex pattern recognition	High accuracy, flexibility	Black box, data hungry
Deep Learning	Multi-dimensional analysis	State-of-the-art performance	Requires large datasets
NLP	Text analysis	Handles unstructured data	Context sensitivity issues
Recommendation	Personalized suggestions	User-centered	Cold start problem

7. Impact on Student Success

7.1 Academic Achievement

Research on the effects of LA and EDM on achievement shows a great deal of potential for enhancing achievement of students. The research of using EDM techniques for predicting student performance and improving learning outcomes showed that courses with high correlation had significant improvement in predicting accuracy, with the F1 score of kNN and neural network being greater than 0.8. (Angeioplastis et al., 2025)

The results of a mixed-methods study on the evaluation of AI-assisted language learning showed that students who were given AI-assisted instruction improved in writing proficiency, motivation, and organization, coherence, grammar, and vocabulary. (Song & Song, 2023)

7.2 Student Engagement

There is evidence that analytics-driven interventions have a positive impact on student engagement in several dimensions. There was a relatively large impact on student participation in learning by using LADs, where several studies suggested medium to large size, which indicates that LADs can encourage students' participation and interaction in online learning environments. (Kaliisa et al., 2023)

The synergy of extended reality technologies and learning analytics and educational data mining can contribute to collaborative learning and social learning, enhance students' self-efficacy and self-regulated learning, and boost students' learning outcomes, grades, learning retention, motivation, and engagement. (Lampropoulos & Evangelidis, 2025)

7.3 Retention

Retention outcomes are an important measure of the effectiveness of LA and EDM. Research shows that regular interaction with AI-generated feedback resulted in a 40% higher retention rate, proving the power of AI-powered smart learning environments in improving educational results. (Naseer & Khawaja, 2025)

7.4 Graduation Rates

There is a clear institutional direction to focus on improving graduation rates, which LA and EDM can help with. Predictive analytics using machine learning can accurately forecast a student's likelihood of graduating with as much as an 80-90% accuracy rate, which allows schools to offer personalized support to help students succeed. (Pelima et al., 2024)

7.5 Learning Outcomes

Beyond performance metrics, LA and EDM can enhance deeper learning outcomes including knowledge construction and skill development. In a systematic literature review that was done on automatic feedback generation, 65.07% of the studies show that automatic feedback positively affects student performance in activities. (Cavalcanti et al., 2021)

7.6 Personalized Support

Student needs can be better met with personalized support, provided by analytics, than by traditional methods. A novel approach based on learning analytics techniques and explainable machine learning techniques has been used to provide students with automatic and intelligent feedback and action recommendations, which supported students' self-regulation in a data-driven manner, with evaluation results showing that the dashboard enhanced students' learning outcomes, helped students self-regulate their learning, and had a positive impact on students' motivation. (Afzaal et al., 2021)

7.7 Student Satisfaction

The quality of implementation and the value of the experience for students depends on student satisfaction with analytics-enhanced learning experiences. The survey of university students showed a positive overall attitude towards the use of generative AI in teaching and learning, and identified several areas where students see potential benefits such as personalized learning support, assistance with writing and brainstorming, and research and analysis. (Chan & Hu, 2023)

Table 6: Summary of Major Empirical Findings

Outcome Measure	Key Finding	Effect Size/Magnitude	Evidence Quality
Academic Performance	Significant improvement with adaptive feedback	28% improvement vs. 14% control	Moderate-High
Engagement	Enhanced participation with LAD use	35% increase	Moderate
Retention	Increased retention with AI feedback	40% increase	Moderate
Prediction Accuracy	ML models predict graduation	Up to 90% accuracy	High
Learning Outcomes	Automatic feedback improves performance	65% of studies positive	Moderate
Cognitive Load	Reduced with AI assistance	22% reduction	Moderate
Satisfaction	Generally positive attitudes	Varies by context	Moderate

8. Emerging Technologies and Future Trends

8.1 Artificial Intelligence

The way that educational analytics are being used is changing with the advent of artificial intelligence, making it more sophisticated in predicting, personalizing, and automating. AI can help solve problems in sustainable education, such as providing better access to quality education, designing personalized learning paths, and assisting with data-driven decision making; AI systems can offer teachers insights on student performance, emotions, and engagement. (Lin et al., 2023)

AI in education has been analyzed in three key areas: personalised learning, intelligent tutoring systems and chatbots, and automated assessment, with studies showing that AI enhances student learning and engagement by providing adaptive feedback and real-time analytics. (Acar et al., 2025)

8.2 Generative AI

Generative AI, specifically Large Language Models, is an educational technology revolution. The emergence of generative artificial intelligence is reshaping higher education, highlighting its versatility and potential applications, as well as students' acceptance of its use, and its ability to enhance learning, while pointing to challenges in the fields of assessment practices, institutional strategies, and risks of academic integrity. (Batista et al., 2024)

While there are opportunities and challenges in the use of transformative artificially intelligent tools like ChatGPT in the sector of education, the effects can be positive or negative, identified questions include those related to knowledge, transparency, ethics, digital transformation, and teaching, learning, and scholarly research. (Dwivedi et al., 2023)

While the promise of widespread use of GPT models is significant, there are concerns in the scientific community about how it can impact analytical abilities and encourage misconduct. The potential for widespread use of GPT models is great, but some scientists are concerned about the impact it could have on analytical skills and the possibility of cheating. (Grassini, 2023)

8.3 Learning Dashboards

Learning dashboards are now more sophisticated and include a range of analytics and visualization features. Although LADs are gaining traction, current LADs are still not widely used to effectively utilize predictive analytics, with studies utilizing predictive analytics only identifying at-risk students and without the use of model interpretation or explainability capabilities. (Ramaswami et al., 2022)

An overview of learning analytics dashboards reveals several research trends: LA research is growing rapidly; it brings inequality and inclusiveness measures to the front; it reveals an unclear path to data ownership and privacy; it provides predictions not clearly translated into pedagogical actions; and possibilities of self-regulated learning are not fully capitalized upon. (Masiello et al., 2024)

8.4 Big Data

The technologies of Big data allow handling of ever larger and more complex educational data. Assessment, individualized learning and precision education are tied to key research areas of big data and AI, including model-driven data analytics approaches that are expanding to inform the development, interpretation, and validation of algorithms. (Luan et al., 2020)

8.5 Explainable AI

Explainable AI is about making analytical models and their predictions transparent. The techniques of Explainable AI (XAI), like LIME and SHAP methods, allow for the interpretation of model predictions for the educational context, and while this is a valid option for simpler models, it is not as straightforward for more complex ones and poses a scope for future research. (Gunasekara & Saarela, 2025)

Explainable machine learning takes the traditional methods one step further: It explains the basis of predictions and offers intelligent recommendations for action supported by data on their own, thereby building trust and meeting the new requirements in the field of regulatory compliance for predictive analytics. (Afzaal et al., 2021)

8.6 Multimodal Learning Analytics

The multimodal learning analytics combines multiple data sources to gain a comprehensive understanding of the learning process. Through a systematic review of methods for multimodal data fusion, MMLA identifies the types of data (digital, physical, physiological, psychometric, and environment) and learning indicators (behavior, cognition, emotion, collaboration, and engagement), and the relationship between multimodal data and learning indicators is complex, which is important for data fusion. (Mu et al., 2020)

8.7 Blockchain in Education

Blockchain can be used to secure credential verification and learning record management. The use of blockchain in education has sparked considerable scientific interest and has the potential to transform the educational system in new ways, such as the ability to issue non-renewable digital certificates, improving systems for certificate verification, and changing the relationship between teachers and students. (Rustemi et al., 2023)

Blockchain's versatility due to its immutable and almost indestructible nature has caught attention for applications where the need for the integrity of identity and content are paramount, with self-sovereign digital identity often cited as a human right that nations need to embrace with conviction. (Grech et al., 2021)

8.8 Digital Twins for Learning

Digital twin technology is a new technology for modelling and simulation of educational environments. The integration of big data analytics and AI/ML techniques with digital twinning enriches its significance and research potential with new opportunities, enabling creation of digital twins or DT-based systems for various applications through systematic review of state-of-the-art deployments. (Rathore et al., 2021)



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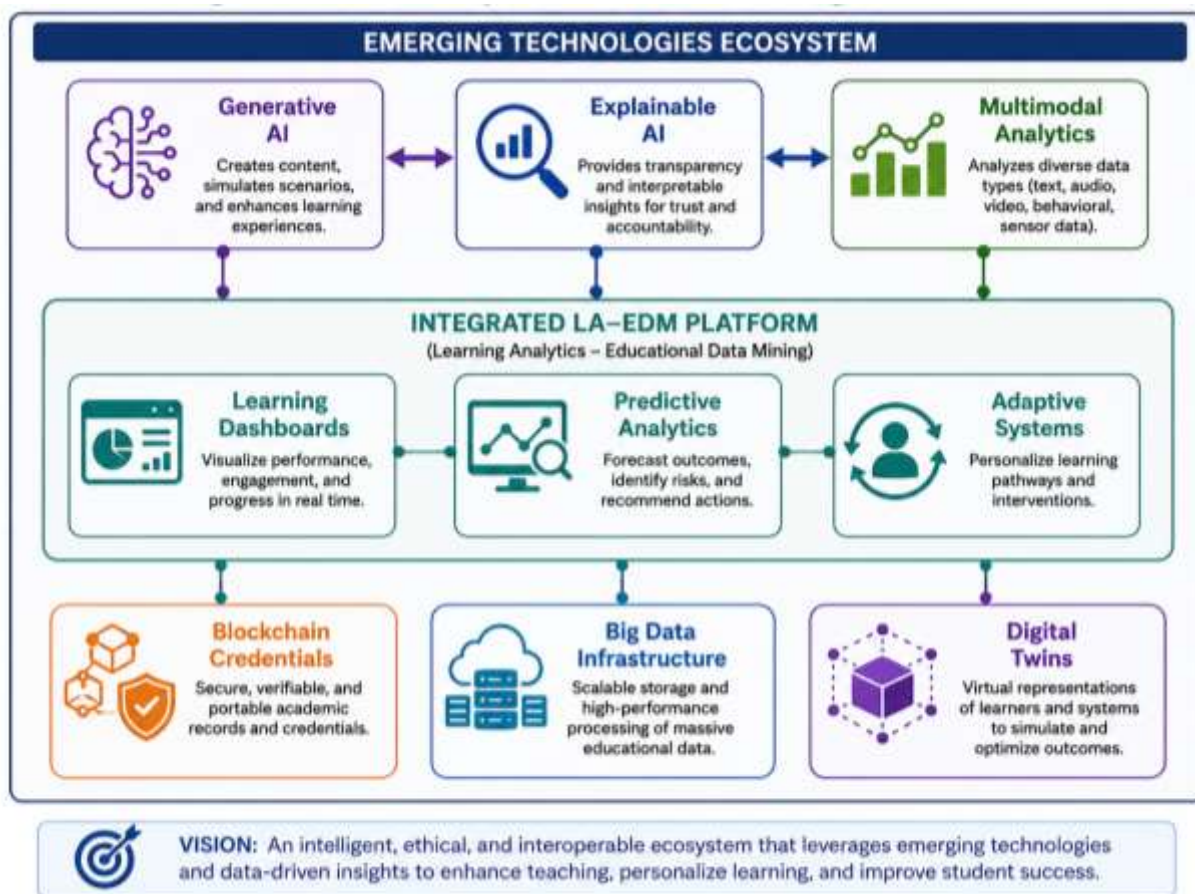


Figure 3: Future Ecosystem of Data-Driven Higher Education

9. Ethical, Legal, and Privacy Challenges

9.1 Data Privacy

Data privacy is the most visible issue related to the implementation of LA and EDM. While learning analytics has matured into a more actionable field, it has also faced many privacy and data protection challenges which have received ample attention, and which it has been suggested could be mapped to a single, unified framework. A systematic review identified eight different and overlapping privacy and data protection issues that span the learning analytics cycle. (Liu & Khalil, 2023)

Privacy and data protection issues need to be viewed in the context of the entire cycle of learning analytics, with stakeholder views on privacy having commonalities across contexts and differences that can arise within the same context. (Liu & Khalil, 2023)

9.2 Data Ownership

Issues of data ownership involve complicated questions of who owns the educational data and how it can be used. As LA and AIED systems grow in scope, questions remain regarding the privacy and agency of the data used, as well as the possibility of design processes excluding stakeholders, which may result in poor alignment and mistrust of the tools. (Alfredo et al., 2024)

9.3 Algorithmic Bias

Algorithmic bias is a serious threat to the perpetuation or exacerbation of educational inequities. Medical biases can creep in and accumulate along the entire AI lifecycle and have serious consequences for clinical care; analogous concerns can be applied to education, where insufficient numbers of samples for some groups can lead to suboptimal performance of the algorithm, underestimation by the algorithm, and clinically meaningless predictions. (Cross et al., 2024)

The practical and ethical concerns with LLMs in education are low technological readiness, lack of replicability and transparency, and insufficient privacy and beneficence considerations, and recommendations are to update existing innovations with the latest LLM and to have a human-centred approach in development. (Yan et al., 2023)

9.4 Transparency

It is important to have transparency about the analytical methods and their use, and to allow for informed consent. The motivation for using AI in Education is aligned with the goal of helping students learn, but there is a need to explicitly address fairness, accountability, transparency, bias, autonomy, agency and inclusion. (Holmes et al., 2021)

Ethical issues are not a simple matter, and the majority of AIED researchers do not have the training to address the emerging ethical issues, so it appears essential to have a well-designed framework for engaging with these ethical issues that takes a multidisciplinary approach and provides strong guidelines. (Holmes et al., 2021)

9.5 Informed Consent

Collecting and using student data for educational analytics is challenging because it requires meaningful informed consent. Solutions to privacy and data protection problems in learning analytics should be more evidence-based which would enhance the trustworthiness of learning analytics and its usefulness, targeting research to be done with stakeholders prior to the implementation of learning analytics. (Liu & Khalil, 2023)

9.6 Student Surveillance

There are ethical issues to consider in how the potential of LA can be used to monitor student behavior. Ethical concerns like private data misuse or surveillance of individuals' lives stand out as one of the most prominent risks of AI in the education sector, as the principle of algorithmic vigilance is suggested to manage, understand and prevent negative outcomes of algorithms in education. (Klímová et al., 2023)

AI has been the subject of debates about automation, algorithmic bias and discrimination, inequality automation, regimes of data-based surveillance and algorithmic profiling, lack of

attention to data protection and privacy, and the authority of tech companies. (Williamson & Eynon, 2020)

9.7 Ethical Governance

Creating strong ethical governance systems is crucial to responsible LA and EDM implementation. At a more general level, there is a need to differentiate between doing ethical things and doing things ethically, to understand and make pedagogical choices that are ethical, and to account for the ever-present possibility of unintended consequences. (Holmes et al., 2021) All stakeholders should be identified, as well as their joint engagement and collaboration to guarantee the ethical use of AI in education, emphasizing the need for joint cooperation and research when using AI-driven technologies with special attention to ethical issues. (Klímová et al., 2023)

Table 7: Major Challenges and Mitigation Strategies

Challenge	Description	Mitigation Strategies
Data Privacy	Protection of student personal information	Privacy-by-design, anonymization, encryption
Data Ownership	Rights over educational data	Clear policies, stakeholder agreements
Algorithmic Bias	Discrimination in predictions	Bias auditing, diverse training data
Transparency	Understanding of analytical methods	Explainable AI, documentation
Informed Consent	Meaningful agreement to data use	Clear communication, opt-out options
Student Surveillance	Inappropriate monitoring	Purpose limitation, data minimization
Ethical Governance	Overall ethical oversight	Ethics committees, guidelines, training

10. Implications

10.1 Implications for Students

LA and EDM have the potential to provide a huge benefit to students in terms of personalized learning, timely feedback, and better structures for support. The students also identified the possibility of individualized learning support, writing and brainstorming support, research and analysis capabilities of AI technologies, but also raised concerns about accuracy, privacy, ethical issues and effects on personal development. (Chan & Hu, 2023)

The research revealed that students tend to use AI assistance rather than learn it, indicating that self-regulated strategies might be effective in bridging the gap in the absence of AI assistance, but not as effective as AI assistance itself. (Darvishi et al., 2023)

10.2 Implications for Teachers

Teachers need to acquire new skills to be able to use LA and EDM and still play an important role in the learning process. Generative language models can offer teachers specific materials and other support, including lesson plans, but teachers must be mindful of the limitations and possible biases of these models, recognize that they are tools to aid teaching and learning, and not replace teachers. (Berg & Plessis, 2023)

AI use in student evaluation suggests that in most research, the pedagogy of educational action is not addressed – with formative assessment being the primary application of AI, which will require teacher training and additional research to grasp the potential of AI in educational assessment. (Calatayud et al., 2021)

10.3 Implications for Administrators

Institutional administrators will have to make decisions that involve numerous considerations for the implementation of LA and EDM, allocation of resources, and policy development. Twenty barriers to digital transformation in higher education have been identified across six broad categories: Environmental barriers, strategic barriers, organizational barriers, technological barriers, people barriers and cultural barriers, which enabled the creation of effective strategies and interventions. (Gkrimpizi et al., 2023)

Data governance for data quality, integrity, and security; analytics for decision making and getting actionable information; stakeholder involvement for collaborative governance; and institutional culture for data-informed decision making are key elements of data-driven governance frameworks. (Kasope et al., 2024)

10.4 Implications for Policymakers

Policymakers need to create structures that allow for innovation, while safeguarding student rights and ensuring equity. The AI Ecological Education Policy Framework deals with the complex impact of AI in university teaching and learning, broken down into three facets: the Pedagogical, focusing on how AI can enhance teaching and learning; the Governance, which covers privacy, security and accountability concerns; and the Operational, which covers infrastructure and training concerns. (Chan, 2023)

There are twenty-one risks in six categories: Discrimination, Hate speech and Exclusion; Information hazards; Misinformation harms; Malicious uses; Human-Computer interaction harms; and Environmental and Socioeconomic harms. (Weidinger et al., 2022)

10.5 Implications for Developing Countries

The implementation of LA and EDM is a unique challenge for developing countries because of resource constraints and infrastructure issues. The digital divide in the field of higher education in developing countries reflects that the costs of digital devices, restrictions in digital infrastructure and digital literacy are the primary factors influencing the digital divide, and that the digital gap negatively affects teachers' pedagogical practice and impacts students' learning engagement and learning outcomes. (Assefa et al., 2024)

The use of AI in educational settings has deepened the digital divide, as there are gaps in access to AI-based learning materials and tools, and limitations in socio-economic resources, digital literacy, and policy frameworks disproportionately affect marginalized communities. (Vesna et al., 2025)

The study on the impact of Covid-19 in education revealed that the education was challenged by poor infrastructures such as network, power, inaccessibility and unavailability, educational institutions and teachers and students should embrace technology and build digital skills. (Onyema et al., 2020)

10.6 Implications for Pakistan

There are certain issues that constitute challenges for higher education sector in relation to the implementation of LA and EDM technologies in Pakistan. The study on attitudes of students in higher education towards digital and distance learning revealed that the desired outcomes of online learning cannot be achieved in underdeveloped countries like Pakistan where most of the students are not able to access internet for various technical and financial reasons. (Adnan, 2020)

The challenges faced by e-learning in Pakistani HEIs are lack of resources, lack of training, lack of infrastructure, lack of e-learning policy, and negative attitude of parents and teachers towards e-learning. (Qazi et al., 2022)

The findings indicated digital divide in Pakistani faculty in terms of faculty access to technology in physical, motivational, skills and usage aspects of faculty in respect of personal and positional categories and there is need to tackle inequalities to ensure effective implementation of LA. (Soomro et al., 2020)

11. Proposed Conceptual Framework

11.1 Integrated Learning Analytics–Educational Data Mining Framework for Student Success Enhancement

This review suggests an integrated LA-EDM framework based on an analysis of literature and gaps identified is the multidimensional nature of student success enhancement processes through data driven approach.

11.1.1 Framework Components

The suggested framework is a five-layered system that will direct the flow from data input to analytics processing to educational outcomes:

Outputs: - Student demographic and background data - Interaction logs in learning management system - Assessment and performance data - Video, audio, physiological data - Survey, reflection data - Student enrollment and course schedules data

Data Sources Layer: - Learning Management Systems (Moodle, Canvas, Blackboard) - Student Information Systems - Assessment platforms - Sensor and IoT devices - External databases (library, career services)

Analytics Layer: Key methodologies include classification, regression analysis, clustering techniques, association rule mining, and Natural Language Processing, facilitating data-driven

decision-making, curriculum development, and customization of learners' experiences. (Papadogiannis et al., 2024)

- Descriptive analytics (what happened)
- Diagnostic analytics (why it happened)
- Predictive analytics (what will happen)
- Prescriptive analytics (what should be done)

Intervention Layer: The framework offers access to LAI infrastructure for academics to test LAIs in their classes, which will incorporate good pedagogical practice and will provide information to academics including students' knowledge gaps or individualised study plans, to support their provision of effective interventions. (Alalawi et al., 2025)

Automated alerts and notifications

- Personalized recommendations
- Adaptive content delivery
- Instructor-mediated interventions
- Peer support facilitation

Student Outcomes: - Academic achievement - Engagement and persistence - Self-regulated learning skills - Satisfaction and well-being - Graduate competencies

Institutional Outcomes: - Retention and graduation rates - Course and program improvement - Resource optimization - Evidence-based policymaking - Quality assurance

11.1.2 Framework Principles

The framework is guided by several key principles:

1. **Human-Centered Design:** Involving stakeholders in every design and deployment stage of LA/AIED systems with a careful balance; involving target end-users, particularly students, to clearly define the human control/automation balance. (Alfredo et al., 2024)
2. **Ethical Foundation:** Distinguishing between doing ethical things and doing things ethically; making pedagogical decisions that are ethical, and considering and being aware of the potential for unforeseen consequences. (Holmes et al., 2021)
3. **Evidence Based Implementation:** It is necessary to have more evidence-based solutions to issues regarding privacy and data protection in learning analytics to make learning analytics more trustworthy and useful. (Liu & Khalil, 2023)
4. **Continuous Improvement:** A key recommendation is for all phases of SRL to be considered when planning interventions to support learning, with comparative research needed to identify the most effective interventions. (Heikkinen et al., 2022)



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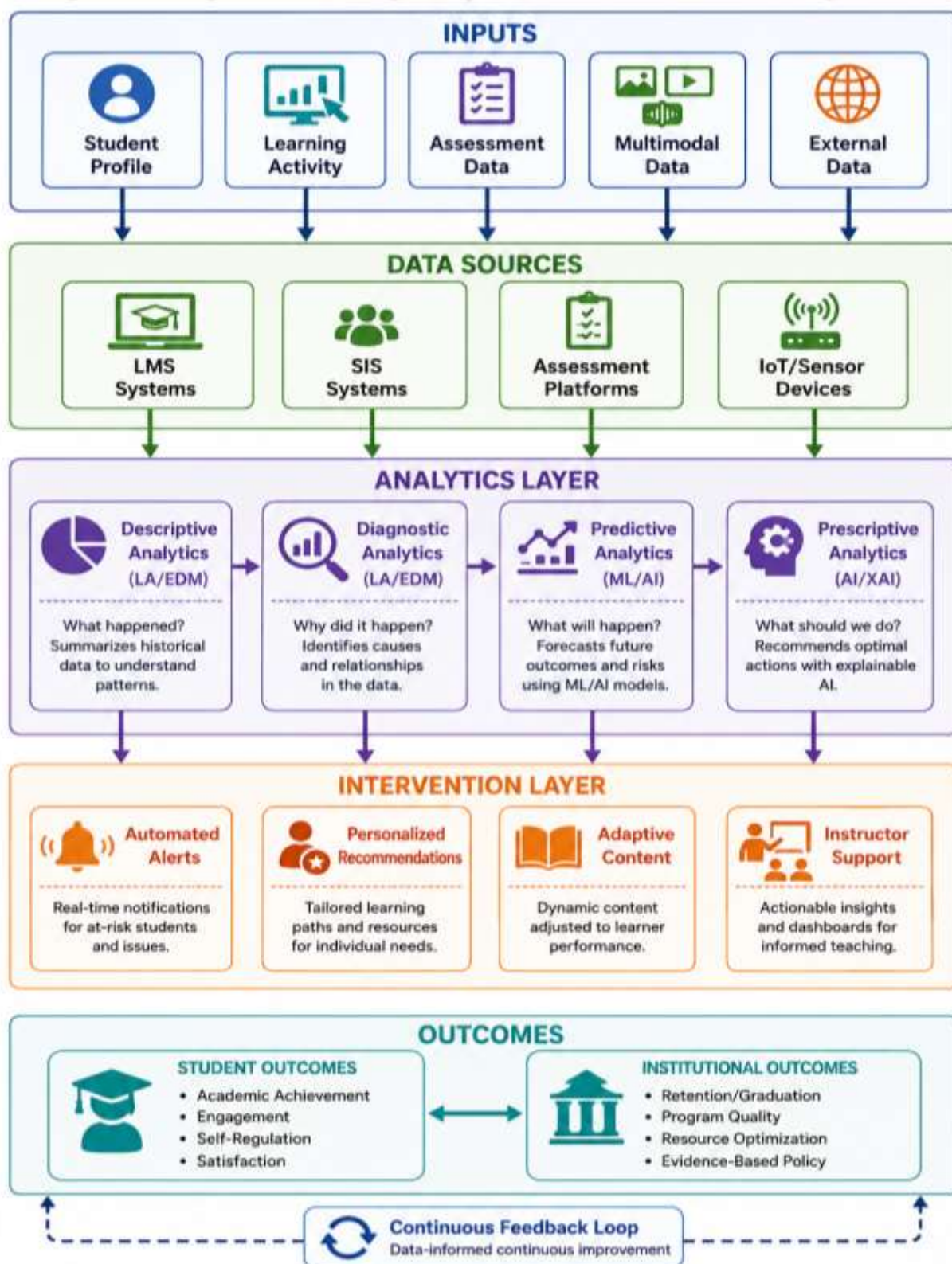


Figure 4: Integrated Learning Analytics–Educational Data Mining Framework

12. Research Gaps

12.1 Methodological Gaps

Despite the progress in LA and EDM studies, methodological problems remain, limiting the generalizability and impact of the results. Common weaknesses in the evaluation of learning analytics dashboards were identified as methodological challenges, including the use of traditional evaluation methods, self-selection bias, assuming that access is synonymous with usage, and the absence of standardized assessment tools. (Kaliisa et al., 2023)

The majority of studies showed very little or no impact on achievement; and there was some limited evidence in well-powered controlled experiments, and many studies only compared users of LADs with non-users, which included students with varying levels of engagement with the dashboard. (Kaliisa et al., 2023)

12.2 Geographic Gaps

The scientific research on LA and EDM is overwhelmingly focused in North America, Europe and limited from developing countries. The digital divide is an increasing contributor to the education gap disproportionately and affects students of marginalized communities who are already experiencing automated inequality the most, thus the need to close the digital divide and diminish its impact on education. (Assefa et al., 2024)

12.3 Policy Gaps

In many contexts there are not yet policy frameworks for governing LA and EDM implementation. The framework should include Pedagogical, Governance, and Operational dimensions to inform stakeholders about their roles and responsibilities and enable them to take the necessary actions to address the multiple implications of AI integration in education. (Chan, 2023)

12.4 Ethical Gaps

There is a significant lack in understanding and addressing the ethical aspects of LA and EDM. The majority of AIED researchers lack training in dealing with new ethical challenges, and a multidisciplinary approach with solid guidelines for ethics appears to be essential. (Holmes et al., 2021)

12.5 Technology Adoption Gaps

The potential impact of LA and EDM innovations is constrained by barriers to technology adoption. The results of the systematic literature review yielded 20 different barriers to digital transformation in higher education, clustered into six barriers groups: environmental, strategic, organizational, technological, people-related, and cultural. (Gkrimpizi et al., 2023)

12.6 Developing Country Gaps

While there are special challenges and opportunities in developing country contexts, research is still quite limited. Strategies to address digital divides in AI-driven learning involve investments

in digital infrastructure, creating affordable AI learning resources, and establishing policies that promote equitable access to technology. (Vesna et al., 2025)

Table 8: Future Research Agenda

Gap Area	Research Questions	Priority
Methodological	What rigorous experimental designs can establish causal effects?	High
Geographic	How do LA/EDM implementations differ across cultural contexts?	High
Policy	What governance frameworks best balance innovation and protection?	High
Ethical	How can algorithmic bias be detected and mitigated effectively?	High
Technology Adoption	What strategies overcome institutional resistance to LA/EDM?	Medium
Developing Countries	What low-cost solutions can address infrastructure limitations?	High
Long-term Impact	What are the sustained effects of LA/EDM on student success?	Medium
Integration	How can LA and EDM be optimally integrated with existing practices?	Medium

13. Conclusion

13.1 Major Findings

This in-depth review has explored the potential of Learning Analytics and Educational Data Mining to improve student success in higher education. The literature synthesis shows that both approaches complement each other and that the use of the unprecedented availability of educational data to understand, predict and enhance learning processes and learning outcomes is a synergy.

Data analytics in higher education offers distinct opportunities to analyse, understand and model the pedagogical processes, as well as to support decision-making process at various levels ranging from individual student to educational system with the unified definition of the pedagogical processes and integrated frameworks. (Nguyen et al., 2020)

There is clear evidence that key applications, such as early warning systems, predictive analytics, and adaptive systems, have great potential to enhance student outcomes. AI-based adaptive feedback has shown to yield a 28% increase in conceptual mastery over a 14% increase in control groups, while engagement increased by 35% and the retention rate improved by 40%. (Naseer & Khawaja, 2025)

13.2 Contributions

This review makes a contribution to the field in that it: Completing a thorough overview of the literature on LA and EDM in higher education in the last two decades. Introducing proposed integrated framework between theoretical and practical aspects 3. Defining ethical, privacy and equity issues that need to be addressed 4. Identifying gaps and future directions for research to inform the field 5. Providing practical take-home messages for a range of audiences

13.3 Practical Implications

This review emphasizes for practitioners the need for using evidence-based methods and considering ethical issues and equity issues. When used wisely, data-driven feedback and intelligent course action recommendations can help enhance students' learning outcomes, support self-regulation and have a positive impact on motivation. (Afzaal et al., 2021)

New tools should be used to help learners understand and trust predictive model behaviour in state-of-the-art dashboards which incorporate machine learning to provide predictive and prescriptive analytics, to meet regulatory needs. (Sušnjak et al., 2022)

13.4 Policy Implications

There is a need for comprehensive frameworks that allow for innovation, but also respect the rights of students and advance equity. Privacy and data protection issues must not be taken lightly anytime during the development of learning analytics; it is a continuous process. (Liu & Khalil, 2023)

Stakeholder engagement should be carefully considered during all design stages of future human-centred LA/AIED systems, and target end-users, in particular students, should be actively engaged. Safety, reliability and trustworthiness should be explored as guiding principles for future LA/AIED systems. (Alfredo et al., 2024)

13.5 Future Directions

Emerging technologies such as generative AI, multimodal analytics, and explainable AI will help to define the future of LA and EDM, and there is a need for continued focus on ethical governance and equity. The paper advocates for a broader approach to AIED that goes beyond considerations on design and development to include educating people about AI and innovating educational systems to remain relevant in an AI ubiquitous world. (Cukurova, 2024)

Conclusions drawn from educational analytics should be used with caution, and governments will focus on promoting lifelong learning, teacher education programs and safeguarding personal information, while the model-driven data analytics approaches will rapidly increase to inform development, interpretation and validation of algorithms. (Luan et al., 2020)

To sum up, Learning Analytics and Educational Data Mining provide strong resources to promote student success in higher education. But unlocking their potential demands careful implementation that embraces innovation while maintaining ethical responsibility, technological capacity, and human judgment; institutional efficiency and student agency. While recognizing

that the core of education remains human, institutions can leverage these tools to build more equitable, effective and engaging learning experiences for all students.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

The authors used generative AI tools, including Large Language Models, to assist with grammar and tone. The specific tool(s) are identified.

Details of the AI usage are given below:

1. Grammarly: To correct grammar and tone
2. Chatgpt To set figures according to my given data

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Conflicts of Interest

The authors do not identify any conflict of interest.

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