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Enabling Adaptive Learning through Data Analytics: A Literature Survey on Applying Machine Learning to Learning Management System Data

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Abstract

This study presents a literature survey on the application of machine learning (ML) in learning management system (LMS) data analytics, aiming to provide insights into adaptive learning development and propose an agenda for future research. The literature survey is based on a proposed adaptive learning framework and critically analyzes the results within this context. The results reveal that machine learning methods can be used to evaluate the effectiveness of instructional interventions and combining online behaviors with textual data can improve the outcome of performance prediction. Key findings also highlight several open issues, including the use of small datasets and the need for comprehensive ML methods and algorithm development. Future research directions are suggested as improving the accuracy of student performance prediction, instructional intervention analysis and recommendation with ML methods, multimodal LMS data analytics, and big data ML approaches for learning behavior pattern detection.

Keywords: adaptive learning, machine learning, LMS, data analytics, literature survey.

1. INTRODUCTION

The digital transformation of education has brought significant advancements in how learning is delivered and managed. Adaptive learning has emerged as a promising technology and a new teaching paradigm in higher education (Xie et al., 2019). Adaptive learning refers to a pedagogical approach that uses technology to provide corresponding educational experiences to individual learners' needs (Li et al., 2021). Adaptive learning environment is personalized to meet the unique needs of individual learners by dynamically adjusting the instruction based on real-time data to optimize the learning process and make it more effective and efficient (Cavanagh et al., 2020). Adaptivity occurs in instructional activities such as the content, the assessment, and the instruction sequence (Castro, 2019) based on learner’s learning performance and learning characteristics. Higher education institutions need to use instructional contents and students’ learning data to conduct adaptive learning systems.

A Learning Management System (LMS) is a

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software application for administering, documenting, tracking, reporting, and delivering educational courses, training programs, or learning and development programs (Elfeky & Elbyaly, 2021; Nizam Ismail et al., 2019). The data generated by an LMS includes learner-generated, teacher-generated, and system-generated data. LMS data contains a wealth of information about learning and teaching behavior and outcomes. As more LMS data becomes available, it is important to improve the capabilities for leveraging this data to gain insights into learning and teaching activities (Tenzin et al., 2020; Zhu et al., 2022). Accordingly, learning analytics using Machine learning (ML) techniques in analyzing LMS data has gained significant attention in the last few years. ML-based learning analytics can provide valuable insights and support for various learning theories and pedagogical interventions by analyzing data generated in educational contexts. Compared to traditional statistical analysis methods, ML methods can provide better accuracy and deal with complexity in data analytics, which provides powerful tools that can inform teaching practices and improve student learning experiences (Riestra-González et al., 2021; Villegas-Ch et al., 2020).

Research has been done on the use of ML in LMS data analytics for enhancing adaptive learning, including delivering learning content, adapting to the individual learner's needs, and providing recommendations for learning paths (Kabudi et al., 2021). In addition, previous studies on ML-based LMS data analytics focus on predicting student performance and analyzing student interactions with LMS platforms to attain perspectives into student discourse in online discussions, identifying at-risk students, and improving student engagement and teaching practices (Gasevic et al., 2014; Korkmaz & Correia, 2019; Tenzin et al., 2020). However, the evidence regarding the potential connection between challenges experienced by students and teachers and the effectiveness of ML-based learning analytics and interventions in resolving these issues, the grounding in relevant theories, the appropriateness of various techniques, and the suitability of the data remains unclear.

This literature survey aims to provide a comprehensive overview of the current state of research at the intersection of machine learning, LMS data, and adaptive learning. In that regard, this study addresses the following research questions: (1) Which ML methods and LMS data are used for various learning analytics objectives/outcomes in existing literature? (2) To what extent are ML-based LMS data analytics interventions grounded in adaptive learning? (3) What are the challenges and future research directions in leveraging ML in advanced learning analytics?

2. METHODOLOGY

Given the demonstrated potential by ML-based LMS learning analytics, we propose a literature survey framework adapted from Peng et al. (2019)'s personalized adaptive learning model. As shown in Figure 1, the adaptive learning route has three levels: "what to learn" - based on the learner's characteristics, "how to learn" - based on the learner's performance, and "how well learned" - based on the learner's personal development (Peng et al., 2019). In each level, three phases of data-driven pedagogical decisions based on ML-based learning analytics represent the ordinate. In the "what to learn" level, learning analytics focuses on learning content analysis and instructional design to tailor the learning resources that can match learners' characteristics. The ML-based analytics process must serve this objective, including LMS data collection, variable selection, ML model determination and training, model performance evaluation and optimization. Moreover, the content may undergo continuous refinement through multiple iterations and incremental adjustments to accommodate the variations and the evolving individual characteristics of learners. In "how to learn" adaptive learning level, the data-driven pedagogies focus on guiding learning activity based on learners' performance (Peng et al., 2019). At this level, LMS data, ML algorithms, and evaluation metrics are determined by learning performance prediction, risk-warning, and learning behavior detection. In "how well learned" level, the data-driven pedagogies focus on expanded learning tasks based on learners' learning progress and personal development (Peng et al., 2019). To achieve this goal, the ML analytics processes need to provide learning path analysis, course enrollment analysis, and dropout rate prediction.

Notably, the three levels of adaptive learning paths do not have the same weight and are not necessarily sequenced as in our model. Thus, our framework can be customized to fit different application contexts. Further, ML-based analytics are iterative processes, which means that based on the analytics outcomes, the LMS data, ML algorithms, and evaluation metrics need to be adjusted and refined multiple times to achieve better performance.

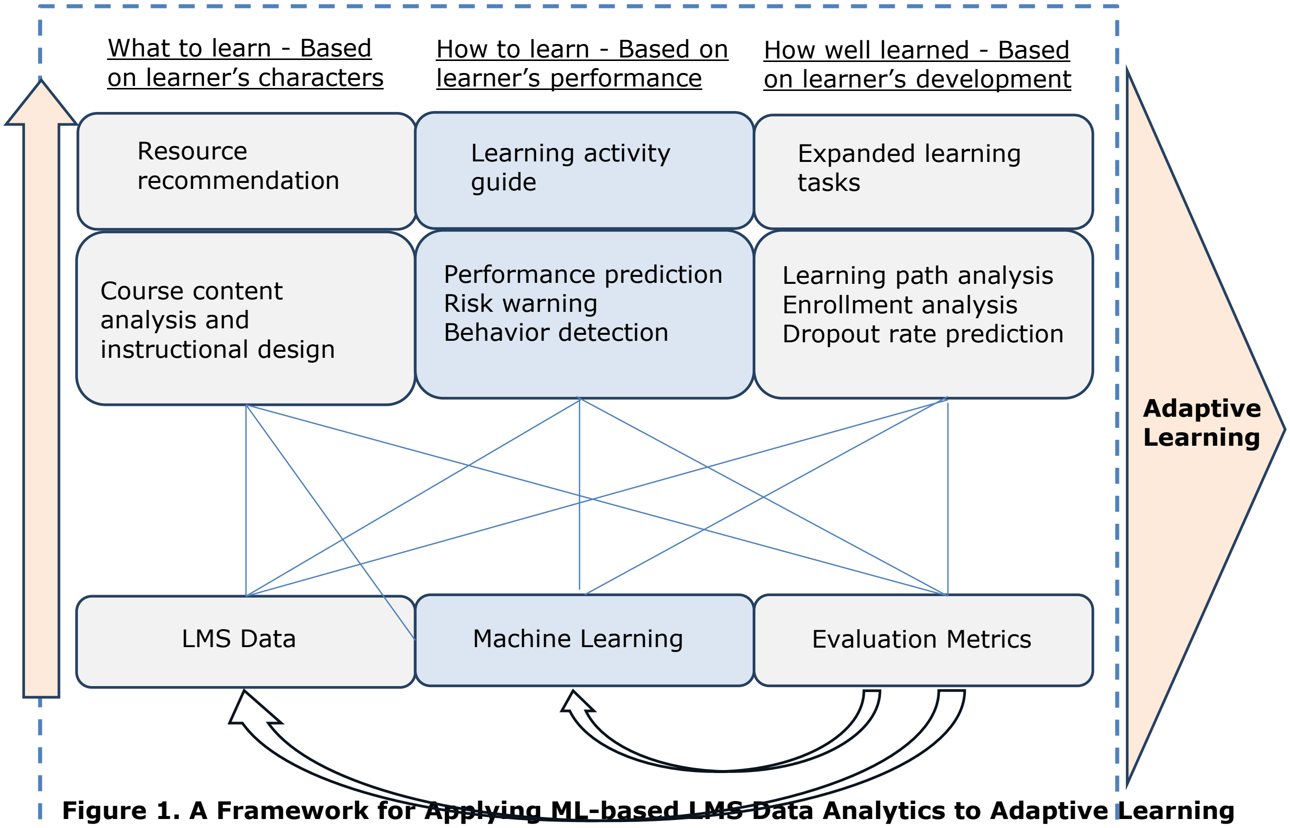

Figure 1. A Framework for Applying ML-based LMS Data Analytics to Adaptive Learning

We searched from five online databases: IEEE Xplore, ACM Digital Library, ProQuest Research Library, ABI/INFORM, and ScienceDirect (Elsevier) using two sets of keywords: ("machine learning" OR "ML" OR "analytics" OR "data analytics") and ("learning analytics" OR "learning management system" OR "LMS"). For each database, we combine these two keywords sets as the search string. Included studies must meet the following criteria: 1. Study of machine learning in LMS data analytics/learning analytics; 2. Full-text paper available; 3. Peer-reviewed paper; 4. Published between January 1, 2013 and January 31, 2023; 5. Written in English. Dissertations/theses, reviews, abstracts, books, book chapters, and reports are excluded for the purpose of this survey. Then, we manually scanned abstracts and filtered out irrelevant articles focusing on education curriculum, pedagogy, impacts, professional development, special external data sources, etc. In addition, we use the snowball technique to identify other relevant papers.

A total of 114 articles were extracted from all online databases. Two authors manually scanned titles and abstracts and filtered out irrelevant articles focusing on education curriculum, pedagogy, impacts, professional development, special external data sources articles based on the inclusion/exclusion criteria, etc. Then we conducted full-text screening. Two authors cross-checked those included articles. In addition, we used the snowball technique to identify other relevant papers in the full-text screening stage. Finally, 52 peer-reviewed academic articles are selected for analysis. These articles are numbered for analysis purpose (see Appendix A).

3. LITERATURE SURVEY RESULTS

Based on our survey framework, we identified the relevant information and extracted it from each paper. For synthesizing the extracted data, we divided the data form into (i) demographic and contextual attributes, (ii) adaptive learning analysis. The first data set was analyzed through statistical techniques and produced descriptive results. The second set of data items was analyzed with a thematic analysis method.

Demographic Distribution

Figure 2 shows the number of the selected papers published per year within the survey period. The number of published studies on the application of machine learning methods in LMS data analytics has been increasing since 2019 and reaches a peak in 2020. 38 papers out of 52 (73%) were published in the past three years signifying the increasing interest possibly due to the rise in online education since the pandemic and the increasing availability of learners' data.

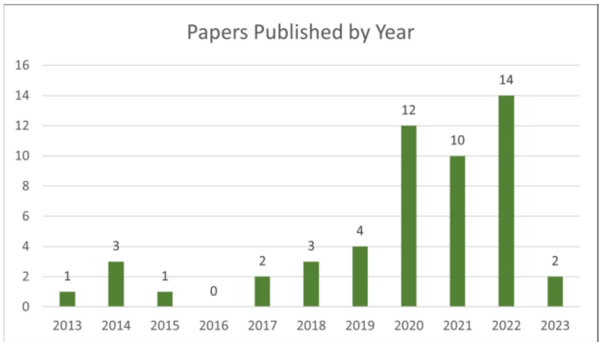

Figure 2: Papers Published by Year

As shown in Table 1, studies were reported from 27 countries. The United States accounted for most of the studies (17% or 9 studies), followed by the United Kingdom, Canada, India, Pakistan, and Greece (3 for each). Our findings are consistent with the prevalence of online education and technology in those countries.

Country	Paper Count	Country	Paper Count
United States	9	Bangladesh	1
Canada	3	Belgium	1
Greece	3	Ecuador	1
India	3	Hungary	1
Pakistan	3	Indonesia	1
United Kingdom	3	Kenya	1
China	2	Korea	1
Brazil	2	Malaysia	1
Croatia	2	Morocco	1
Japan	2	New Zealand	1
Spain	2	Philippines	1
Taiwan	2	Switzerland	1
Vietnam	2	Turkey	1
Australia	1		

Table 1: Distribution by Country

Analysis Based on Proposed Framework
Distribution of Papers by LMS Data Type. Table 2 shows the distribution of the 52 studies by LMS data type. Assessment data has been the most often utilized (27 papers or 52%). The following are learner's data (25 or 48%), user activity data (20 or 38%) and behavior log data (17 or 33%).

LMS Data	Articles	#	%
Assessment data - question and grade related to assignment, test, quiz, exam, etc.	P1,P4,P6,P7,P9,P10,P12,P14,P18, P19,P21,P23,P24,P27,P30,P31,P32,P33,P36,P39,P40,P41,P43,P44, P45,P46,P50	27	52
Leaner Demographic data and socioeconomic data - age, gender, location, device, enrolment, income, etc.	P4,P6,P7,P9,P10, P11,P12,P13,P15,P19,P25,P27,P30,P31,P32,P33,P36,P39,P40,P41, P43,P45,P46,P48,P52	25	48
Activity data - submissions, comments, posts, etc.	P1,P3,P4,P6,P8,P10,P13,P16,P18, P22,P23,P24,P26,P30,P32,P42,P44,P46,P48,P51	20	38
User behaviour log - navigation, page views, time spent on the platform, etc.	P6,P11,P14,P15, P17,P22,P25,P26,P28,P29,P33,P34,P37,P38,P45,P49,P51	17	33
Course Information - content webpage, instructor, start/end date, number of students, etc.	P4,P15,P16,P18, P20,P21,P26,P28,P30,P32,P33,P35,P37,P38,P50,P51	16	31
Interaction data - discussions, forum posts, announcements, messages, etc.	P2,P3,P9,P10,P22,P24,P26,P30,P44,P47,P48,P49, P51	13	25
Multi-modal data - audio, video, presentation, sensor signal, body posture and hand gesture, etc.	P2,P5,P20,P29,P47,P48,P52	7	13
Learning progress data - time spent on each module, the percentage of course completion	P13,P33,P35,P38,P49	5	10

Table 2. Distribution by LMS Data Type

Distribution of Papers by Machine Learning Approach. Table 3 shows the distribution of the 52 studies by machine learning method. Overall, SVM and Random Forest are the most often used machine learning methods (24 papers or 46% for each), followed by Logistic Regression (17 or 33%), Decision Tree (16 or 31%), and MLP Neural Network (14 or 27%).

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Machine Learning	Articles	#	%
Support Vector Machine (SVM)	P3,P5,P6,P7,P9,P13,P15,P17,P22,P30,P31,P32,P34,P35,P36,P39,P40,P41,P43,P45,P46,P48,P52	24	46
Random Forest (RF)	P1,P6,P7,P9,P10,P11,P15,P17,P18,P20,P27,P29,P30,P32,P33,P35,P36,P38,P39,P40,P42,P48,P51,P52	24	46
Logistic Regression (LR)	P4,P6,P9,P12,P17,P22,P24,P25,P30,P33,P34,P40,P41,P42,P45,P46,P49	17	33
Decision Tree (DT)	P1,P3,P10,P11,P12,P15,P18,P26,P28,P34,P36,P39,P40,P46,P47,P51	16	31
MLP Neural Network (MLPNN)	P3,P9,P11,P13,P18,P19,P23,P28,P30,P34,P43,P44,P45,P46	14	27
KNN	P1,P7,P9,P11,P12,P22,P28,P30,P32,P33,P41,P46,P48	13	25
Naïve Bayes (NB)	P1,P6,P11,P18,P32,P33,P34,P40,P41,P42,P43,P49,P52	13	25
Clustering - K-means	P8,P16,P25,P27,P47,P49	6	12
Bayesian Network (BN)	P11,P21,P22,P28,P30	5	10
Gradient Boosting Machine (GBM)	P5,P11,P15,P40,P46	5	10
Linear Regression (LR)	P38,P39	2	4
BERT	P29,P50	2	4
Radial Basis Function Neural Network (RBFNN)	P3,P11	2	4
AdaBoost	P9	1	2
GPT3	P50	1	2
Long Short-term Memory (LSTM)	P46	1	2
Reinforcement Learning	P37	1	2
Bagging	P1	1	2
Convolutional Neural Network (CNN)	P15	1	2
RIPPER or JRIP	P18	1	2

Table 3. Distribution by ML Approach

Distribution of Papers by Analytics Outcome. Table 4 shows the distribution of selected papers by objectives/outcomes. Learning performance analysis/prediction is the most popular, being used in 27 studies (52%), followed by learning behavior/style detection and analysis, used in 17 studies (33%), learning path and recommendation (29% or 15 studies), then course delivery and instructional design (19% or 10 studies), and student enrollment, retention or dropout rate prediction, used in 13% of studies.

Analytics Outcome	Articles	#	%
Learning performance analysis/prediction	P1,P6,P7,P9,P10,P12,P13,P15,P17,P18,P20,P21,P22,P24,P25,P26,P27,P28,P30,P31,P32,P33,P34,P39,P43,P45,P46	27	52
Learning behavior/style detection and analysis	P2,P3,P8,P11,P14,P16,P23,P26,P29,P32,P43,P44,P47,P48,P49,P51,P52	17	33
Learning path and recommendation	P3,P9,P13,P14,P16,P21,P24,P29,P30,P35,p37,P38,P44,P48,P50	15	29
Course delivery and instructional design	P5,P14,P19,P20,P25,P35,P38,P42,P44,P50	10	19
Enrollment, retention, and dropout rate prediction/analysis	P4,P10,P17,P36,P40,P41,P46	7	13

Table 4. Distribution by Analytics Objective/Outcome

Distribution of Papers by Evaluation Method. As shown in Table 5, accuracy is the most often used evaluation metric in LMS data analytics with ML approaches (34 out of 52 or 65%). This is followed by F1-score, used in 27% (14 of 52), then AUC-ROC (21% or 11 papers), then Precision and Recall (19% or 10 papers), and RMSE/MSE/MAE metric (13%, 7 out of 52). Table 6 shows the use of analytics outcomes evaluation methods. 73% of studies do not clearly employ

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the analytic outcomes evaluation method. Benchmarking is the most used (12%, 6 papers), followed by collecting learners' feedback (8%, 4 papers) and designated assessment (4%, 2 papers). Further, the statistical analysis and prescriptive analysis is used for analytic outcomes evaluation (one paper for each).

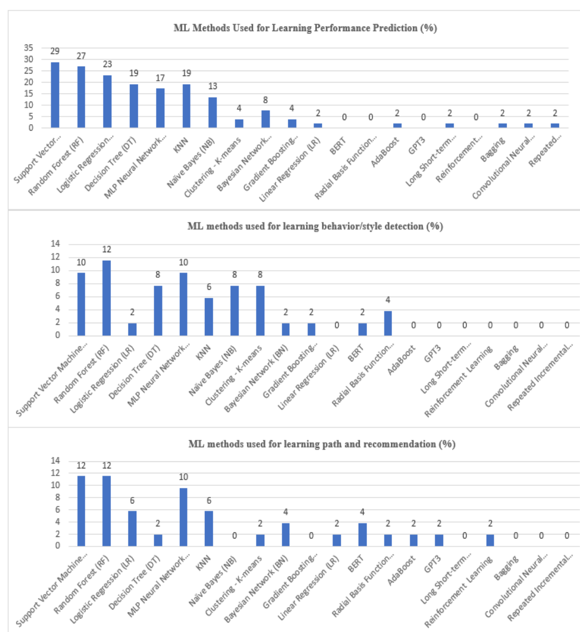
Evaluation Metric	Articles	#	%
Accuracy	P1,P3,P6,P7,P10,P11,P12,P13,P15,P18,P19,P20,P21,P23,P24,P26,P27,P28,P29,30,P32,P34,P35,P36,P38,P41,P43,P44,P45,P46,P47,P48,P51,P52	34	65
F1-score	P4,P7,P12,P17,P23,P29,P33,P36,P37,P40,P42,P48,P49,P51	14	27
AUC-ROC	P6,P7,P20,P23,p27,P30,P34,P41,P46,P48,P51	11	21
Precision and Recall	P7,P12,P17,P23,P27,P40,P46,P48,P49,P51	10	19
RMSE/MSE/MAE	P9,P22,P25,P31,P37,P39,P44	7	13

Table 5. Distribution by Evaluation Metric

Analytic Outcomes Evaluation Method	Articles	#	%
Benchmarking	P4,P14,P17,P21,P31,P37	6	12
Collecting learners' feedback	P2,P25,P44,P51	4	8
Specially designed assessment	P19,P48	2	4
Statistical analysis - ANOVA	P34	1	2
Prescriptive analysis	P32	1	2
No analytic outcomes evaluation methods clearly mentioned	P1,P3,P5,P6,P7,P8,P9,P10,P11,P12,P13,P15,P16,P18,P20,P22,P23,P24,P26,P27,P28,P29,P30,P33,P35,P36,P38,P39,P40,P41,P42,P43,P45,P46,P47,P49,P50,P52	38	73

Table 6. Distribution by Analytics Outcomes Evaluation Method

Distribution of ML Methods and LMS Data Used for Analytics Outcomes. As shown in Figure 2 and Figure 3, i) the most often used ML methods for learning performance prediction is SVM and Random Forest, and the most often used LMS data is learner demographic data and assessment data; ii) for learning behavior/style detection and analysis, Random Forest, MLP Neural Networks, and SVM are the most popular ML methods and the LMS data is learners' data and activity data; iii) for learning path and recommendation, top three most often used ML methods are SVM, Random Forest, and MLP Neural Network. The LMS data is assessment data, activity data, and course information; iv) for the outcome of course delivery/instructional design, Random Forest, MLPNN, LR, and SVM are commonly used with LMS assessment data, course information, and user behavior log data; v) for student retention/dropout rate prediction, SVM and LR are equally most popular used ML algorithms, and the LMS data is the combination of learner demographic data, assessment data, and activity data.



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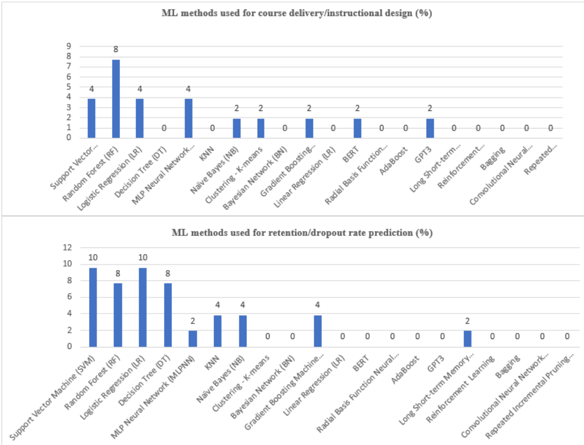

Figure 3. Distribution of ML Approaches Used for Analytics Outcomes

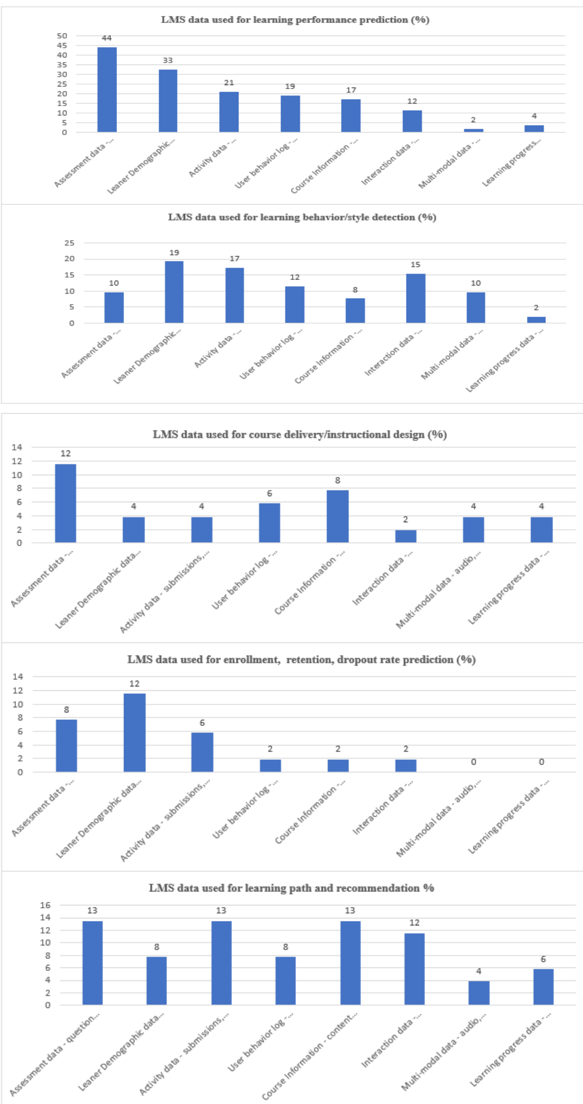

Figure 4. Distribution of LMS Data Used for Analytics Outcomes

Distribution of Evaluation Metrics by ML Methods. As shown in Table 7, accuracy is the most often used evaluation metric for all top six ML-algorithms.

ML Methods	Accuracy	Precision / Recall	F1- Score	AUC-ROC	RMSE / MSE	Cross-validatio
SVM	15	5	5	6	4	5
Random Forest (RF)	18	6	9	7	2	7
Logistic Regression (LR)	8	5	7	5	2	2
Decision Tree (DT)	14	4	4	3	0	2
MLP Neural Network (MLPNN)	13	2	1	4	2	2
KNN	12	4	4	5	2	4

Table 7. Distribution of Evaluation Metrics on Top Six ML Algorithms

In extant studies, researchers used multiple metrics instead of a single metric to assess the effectiveness and efficiency of utilized ML approaches. Notably, AUC-ROC is the second most popular utilized for SVM, followed by RMSE, Cross-validation, and F1-Score. for random forest, logistic regression, decision tree, neural networks, and KNN methods, F1-score, followed by Precision/Recall, AUC-ROC is the most popularly used evaluation metrics other than Accuracy.

4. DISCUSSION AND FINDINGS

Following the proposed review framework, we summarize primary challenges and issues in the current literature as shown in Figure 4. These findings cover the different levels of adaptive learning paths: LMS data (what to learn), machine learning methods (how to learn), analytics outcomes and evaluation (how well learned). Most extant studies use relatively small datasets to train ML models. Such datasets primarily focus on course-level cross-section numeric data (Du et al., 2020). However, the data generated from the LMS platform nowadays is large, multimodal longitudinal data. Machine learning in the context of big data presents unique challenges, and overcoming these obstacles requires approaches that differ from traditional learning methods. Scalable, multidomain, parallel, flexible, and intelligent

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learning methods are preferred in this context (Qiu et al., 2016).

Secondly, existing literature lacks a comprehensive machine learning (ML) method or a combination of methods designed to achieve specific analytics outcomes (Islam & Mahmud, 2020). The focus has primarily been on using existing ML methods and comparing the performance, with a lack of new algorithm development. For example, over 40% of reviewed studies use SVM but rarely combine it with other ML methods or optimize it to achieve better analysis accuracy. Notably, neural networks and some emerging ML methods such as LSTM, BERT, and GPT are gaining more and more attention and need deeper investigation in the domain (Pan et al., 2020; Yang, 2021). Furthermore, the development of robust methods for feature selection and assessing their effectiveness is a promising direction in the domain (Coussement et al., 2020; Soleimani & Lee, 2021).

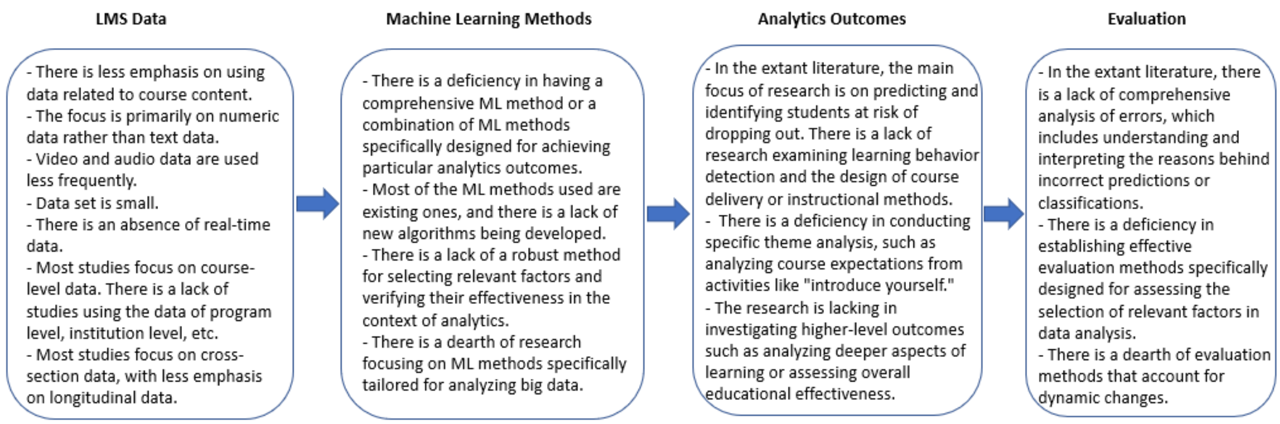

Figure 4. Challenges and Issues in Current Literature

Regarding analytics objective/outcome, the primary emphasis is on forecasting learners' performance and detecting learners who are likely to discontinue their studies (Villegas-Ch et al., 2020). Less attention has been given to investigating the identification of learning behaviors and the development of instructional techniques for course delivery. There is a dearth of research regarding the text analysis of specific themes, such as evaluating course expectations through activities like "introduce yourself" (Tran et al., 2022). Additionally, the current body of research is limited regarding the exploration of various outcomes, including the examination of more profound facets of learning and the assessment of overall educational effectiveness (Yang, 2021).

With respect to evaluation metrics, extant literature lacks a comprehensive examination of errors, including a thorough understanding and interpretation of the underlying causes for inaccurate predictions or classifications. Moreover, there is a gap in defining evaluation methods that effectively assess the selection of pertinent features in data analysis (Lan et al., 2014). Further, there is a scarcity of evaluation methods that adequately consider dynamic changes (Yang, 2021).

Based on the abovementioned challenges and issues, there are several important directions for future research in this domain. First, student performance prediction remains a viable research topic in the domain (Jiao et al., 2022; Riestra-González et al., 2021). Even though many studies have been done on the utilization of various ML methods in student performance prediction, there remains a need for robust predictive models with good generalizability for different courses, programs, and institutions.

A general predictive model can be developed using existing machine learning algorithms, or combining multiple algorithms, or newly created algorithms. For example, recent advancements in text mining with ML methods have prompted researchers to utilize social media to predict learning performance (Shahbazi & Byun, 2020). However, in the field of LMS data analytics, there is a scarcity of studies that have effectively integrated online behaviors with textual data to enhance prediction accuracy. Therefore, it is crucial to combine online behaviors with textual data to improve the outcome of performance prediction.

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Second, machine learning methods can be used to evaluate the effectiveness of instructional interventions including course content delivery and instructional design. Due to the lack of an educational framework, there is no consistent results that can be extracted from the studies of instructional content and design (Lee, 2021; Tran et al., 2022). Well-designed instructional content has a significant impact on enhancing learning effectiveness. Consequently, it is anticipated that more researchers will focus on identifying content design patterns in the future. However, current studies have not emphasized the automated support for teachers and learners to improve their teaching and learning experiences, such as offering automatic suggestions for instructional design or adjustments to learning strategies (Du et al., 2020).

Third, newer LMS platforms include many user interaction features, such as discussion boards, announcement portal, conversation tools, collaboration tools, etc., aimed at improving student engagement and teaching performance. These advanced tools generate large volumes of text, video, and audio data. Extant literature is limited in regard to the use of ML methods with text or other types of data (Shahbazi & Byun, 2020). One of the important directions for future studies is to investigate the utilization of appropriate ML methods for LMS multimodal data analytics. For example, one study investigated students' learning motivation and predicted their learning performance using video-viewing data in a flipped statistic course (Liao & Wu, 2023).

Fourth, the application of big data ML approaches in the detection of learning style and behavior. LMS platforms have been used for more than ten years. An individual institution possesses a large volume of longitudinal learners' activity and log data. Also, this big data can include various types and formats. How to gain valuable insights into learners' behavior patterns by using ML methods in this big data analytics context is an attractive direction for future research. For example, how many learning patterns are needed to train a classifier depends on achieving a balance between cost and accuracy when dealing with overfitting issues (Bird et al., 2022).

5. CONCLUSIONS

This study identified, organized and discussed challenges and issues related to the application of ML in analyzing data from LMS into four perspectives according to the proposed literature analysis framework. Findings indicate that extant research often uses small datasets and focused on numeric data, while LMS platforms generate large multimodal longitudinal data. Future research directions include student performance prediction, instructional intervention analysis, multimodal data analytics, and big data ML approaches for learning style and behavior detection.

Overall, the application of ML in LMS data analytics has significant potential to improve teaching and learning outcomes. Institutions can implement adaptive learning platforms that adjust the delivery of content based on student data collected from the LMS. ML models can dynamically suggest content adjustments (e.g., additional resources for struggling students or advanced materials for high-performing students). The proposed research agenda focuses on a range of research questions and machine learning methods that can be used to advance the field. By addressing these questions, researchers can develop a deeper understanding of the utilization of machine learning approaches in learning analytics as well as the development of advanced solutions. While there is a natural inclination to rely on existing methods in the field, it is essential to pursue a parallel line of research that develops new methods and systems.

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APPENDIX A
Articles Coded for Literature Survey

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(Dervenis et al., 2023)	Predicting Students' Performance Using Machine Learning Algorithms	P7
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(Lagman et al., 2020)	Integration of Neural Network Algorithm in Adaptive Learning Management System	P19
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