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SYSTEMATIC LITERATURE REVIEW ON THE USE OF MACHINE LEARNING IN ONLINE LEARNING IN THE CONTEXT OF SKILL ACHIEVEMENT

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ABSTRACT

Online education has experienced significant progress, with machine learning playing a crucial role in improving the outcomes of skills acquisition. In this examination of scholarly literature, we analyze research focused on the use of machine learning in online education, aiming to achieve specific skills. The results of this comprehensive literature review reveal a wide range of machine learning applications, including adaptive modeling, personalized content, automated grading, and student progress forecasting. This approach has enhanced the effectiveness of online education by providing a more targeted and personalized learning experience for each student. Additionally, several studies demonstrate notable improvements in skill acquisition, as indicated by various measures. However, challenges arise regarding data privacy, model accuracy, and the need for validating outcomes in real-world contexts. Therefore, this systematic literature study presents a comprehensive overview of the implementation of machine learning in the field of online education, with the ultimate objective of skills acquisition. This investigation offers valuable insights into the potential and limitations associated with the use of machine learning in online education. These insights will greatly benefit educators, researchers, and developers of educational platforms in understanding how this technology can be utilized to enhance students' proficiency in the continually evolving landscape of online learning.

Keywords: *Skill, Online Learning, Education, Machine Learning, Learning Analytic*

1. INTRODUCTION

Online learning has become a widely utilized educational tool in contemporary times due to its facilitation of flexible time and location. Students are no longer required to physically meet with their instructors, as the latter can provide instructional materials that can be accessed and completed by students at their own convenience. Online learning platforms, specifically learning management systems, are employed by numerous higher education institutions to facilitate virtual education. Nonetheless, online learning often fails to equip students with the necessary skills outlined in traditional offline courses. This issue arises primarily due to a lack of alignment between predetermined learning outcomes and the practical skills demanded in the professional realm. Furthermore, higher education institutions and instructors struggle to effectively evaluate and assess the achievements of students on online learning platforms.

Nevertheless, various countries are currently endeavoring to address this predicament through empirical research and the provision of guidelines aimed at cultivating skills that align with the demands of the workforce. These efforts seek to establish a harmonious connection between the higher education curriculum and the practical needs of the professional sphere, as exemplified by initiatives in the Netherlands [1], Sub-Saharan Africa [2], Italy [3], Russia, America and China [4].

In addition to this, the learning management system possesses numerous attributes that enable the mapping of student activities during online learning endeavors, all in pursuit of achieving the desired learning outcomes. Nonetheless, higher education often encounters difficulties in properly aligning the learning management system attributes with the various student activities, such as the completion of

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quizzes and assignments, engagement with reading materials, video consumption, and other related activities.

Machine learning has become widely embraced within the field of higher education due to its efficacy in addressing challenges. Machine learning encompasses a diverse range of tools that effectively facilitate the extraction, analysis, and interpretation of a wide array of observable phenomena, enabling valuable insights to be gained [5].

In the realm of higher education, machine learning is extensively utilized, particularly in the realm of mapping student learning outcomes, both in the online and offline context. This utilization allows universities to acquire valuable insights into decision-making processes and the enhancement of the quality of education [6],[7],[8],[9],[10].

The proficiency of students is commonly assessed based on their achievement of learning outcomes, as demonstrated by their grades and abilities. Machine learning has been empirically proven to yield favorable results in the mapping of student performance [11],[12],[13],[14] which ultimately determines the success of their learning journey. Among all the factors at play, student performance is regarded as the key determinant in the attainment of learning outcomes. It is worth noting, however, that the effectiveness of a machine learning model in producing accurate mapping results is contingent upon numerous factors and conditions [15].

Factors and conditions that determine the success or failure of a machine learning model in the process of mapping student performance [15] encompass various aspects. These include the selection of learning features, the choice of indicators, the level of difficulty in the course being undertaken, the methodology employed in teaching the machine, and the time interval between training the model and forecasting its outcomes.

The learning features and indicators, once identified, are transformed into datasets that are subsequently utilized as training and testing datasets within the machine learning model. Inaccurate selection of these datasets, as well as the machine learning model itself, can lead to inaccurate mapping results. This misalignment with the desired objectives can ultimately result in errors in mapping student performance and impede the success of students in acquiring the necessary skills aligned with the learning outcomes.

This review seeks to examine the role of machine learning in addressing these challenges. It acknowledges that machine learning techniques offer potential solutions by analyzing the activities and performance of students, providing valuable insights for decision-making processes, and enhancing the overall quality of education. The review emphasizes the importance of carefully selecting appropriate learning features and indicators for machine learning models to ensure accurate mapping results. This requires considering factors such as the complexity of the course, teaching methods, and the time intervals between training and forecasting.

Considering these challenges, it is imperative to address several key questions. This is particularly crucial in determining the appropriate features and learning indicators for machine learning models, which can effectively guide students towards achieving the desired skills as outlined in the learning outcomes. The research questions for this study are as follows:

1) How is machine learning applied in the context of online learning? This review aims to examine the utilization of machine learning in online learning, focusing on research objectives, models and approaches employed, as well as the methodology and results attained.

2) What are the various machine learning techniques utilized in machine learning-based online learning? This review aims to identify the learning elements, indicators, algorithms, and evaluation metrics that are employed, specifically in the context of mapping skill achievement.

3) How can skill attainment be enhanced in machine learning-based online learning? This review aims to explore strategies for improving skill attainment by leveraging machine learning techniques within online learning environments.

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2. GUIDELINE FOR SKILL ACHIEVEMENT

To acquire competencies, it is essential to establish mutually agreed-upon arrangements among the government, industry, and institutions of higher education. These arrangements will serve as guidelines for the attainment of skills and the evaluation thereof. One such arrangement is the "Indonesian National Qualifications Framework," which has been implemented by the government of Indonesia as a fundamental framework for all fields of industry and academic study. Specifically, within the realm of Computer Science, the Indonesian government, represented by the Ministry of Industry, the Ministry of Manpower, and the Ministry of Communication and Information Technology, in collaboration with the Informatics and Computer Higher Education Association, has developed a Catalog of Occupational Competency Units within the Indonesian National Qualifications Framework in the domain of Information and Communication Technology (ICT)[16]. For instance, these provisions outline the essential skills and contextual understanding necessary for an individual to be considered an "expert programmer," both within the professional realm and as a requirement for higher education learning outcomes.

Table 1: Competency Unit and Assessment Context of Expert Programmer According to List of Occupational Competency Units in The KKNI Information and Communication Technology Sector.

KKNI Competency Unit	Assessment Context
Designing the user experience	Giving cases of developing algorithms or programming with a certain language (practice).
Design application architecture	Hands-on practice and written test of application architecture design according to requirements.
Implement problem solving into subroutines	Testing is given in the form of practice solving problems in the representation of algorithms or flowcharts or pseudocode or examples of input output, or other similar representations.
Implement structured programming	Demonstration/practice of knowledge, skills and attitudes required work.
Implements object-oriented programming	Demonstration/practice of required work skills.
Implement programming algorithms	Request an example of input, output which is then represented in programming algorithms.
Create program code documents	Provision of cases (practice) source documents and supporting documents (requirement specifications).
Migrating to new technology	Conceptual interviews and demonstrations to actualize the implementation of the work.
Debugging	Written tests without tools (by being given source code containing bugs and tested to find them) or with tools.
Perform program profiling	Direct practice or written test equipped with tools, equipment, programs to be profiled and optimization targets and supporting documents (need specifications).
Provide technical instructions to customers	Conceptual interviews and demonstrations to actualize the implementation of the work.
Execute application cutover	Direct practice or written test equipped with equipment, tools, and existing applications as well as new applications that will be replace.
Carry out software configuration according to the environment (development, staging, production)	Hands-on practice equipped with the equipment; equipment needed.
Implement an alert notification if the application has a problem	Direct practice is equipped with tools, equipment, applications, and simulation of problems that will occur.
Perform software updates	Hands-on practice equipped with tools, equipment, existing software and updated

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The principal aim of this paper is to present a comprehensive examination of the characteristics, indicators, models, and evaluation metrics employed by preceding researchers. Furthermore, this investigation will offer a comprehensive overview of the approach adopted by researchers to enhance the acquisition of expertise in online learning by incorporating features, learning indicators, and machine learning algorithms with the Competency Unit and Assessment Context from Expert Programmers.

3. METHOD

To analyze the role of machine learning in the learning management system platform in the context of online education, a systematic review of the literature was conducted. The selection process for this review consisted of five stages. The initial stage involved conducting a general search of databases to explore the application of machine learning approaches in online education. The subsequent stage focused on refining the search to align with predetermined criteria specific to machine learning approaches in online education. Following this, a more rigorous selection stage was implemented to exclude papers that did not meet additional criteria, ensuring the accuracy of the search results. The fourth stage involved presenting the findings, elucidating the utilization of machine learning in online education and its implementation for skill development. Lastly, the concluding stage entailed drawing conclusions based on the outcomes of this study.

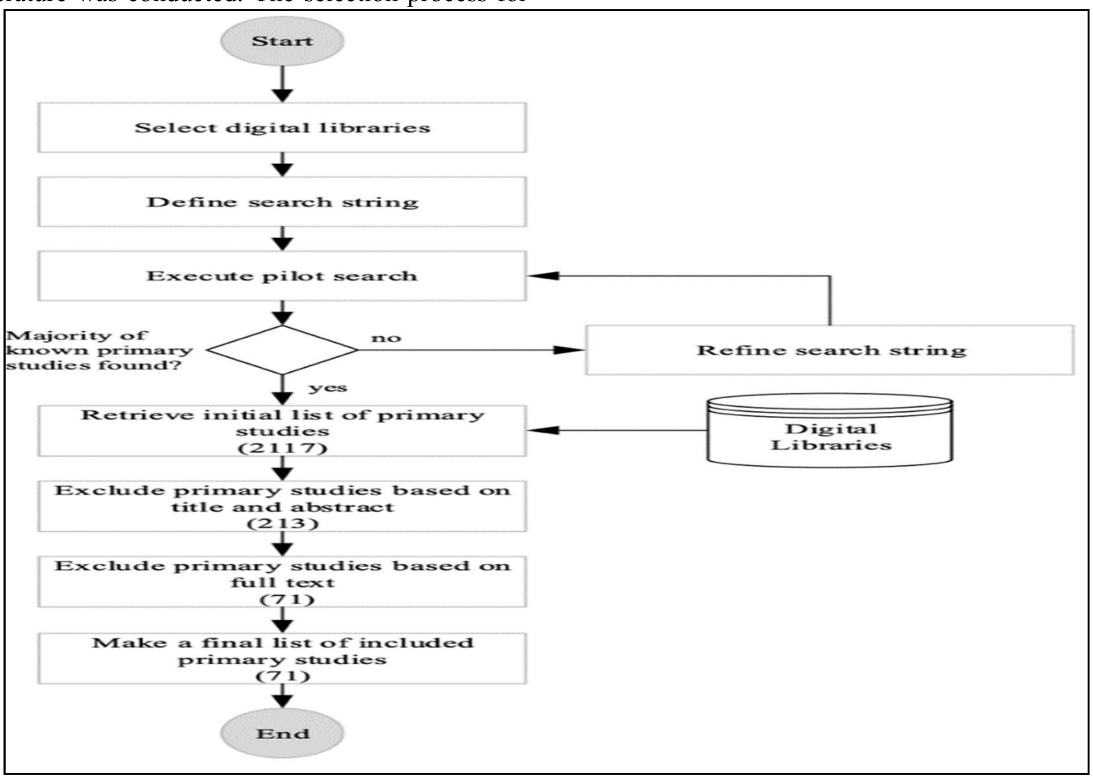

Figure 1: Search Strategy [17]

3.1 General Database Searching

The digital repositories employed in this study include Emerald, IEEE, Science Direct, Springer, and World of Science. The search queries employed across all repositories are "machine learning" AND ("online learning" OR "eLearning" OR LMS) AND ("skills" OR "learning outcomes") AND student. The timeframe for the selected articles ranges from 2019 to 2023. The tabular presentation below illustrates the outcomes derived from the search results in the chosen Digital Library:

Table 2: Result from Database.

Digital Libraries	Total Result
Emerald	113 Article
IEEE	5 Article
Science Direct	92 Article
Springer	143 Article
World of Science	4 Article

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3.2 Focus Searching

Following the acquisition of literature from the digital library, the subsequent step is to proceed with the selection of articles in accordance with the initial screening criteria delineated in table 3.

Table 3: Focus Searching.

#	Screening Criteria
1	Focus on applying machine learning to analyze learning outcomes in online learning, not conventional learning
2	Includes studies empirically
3	The research methodology is clearly explained
4	Articles clearly describe the learning features, algorithms and machine learning models used along with evaluation metrics.
5	Research papers

3.3 Excluded Paper

The review conducted in this research excludes papers that fall within the categories enumerated in table 4, featuring the following criteria:

Table 4: Selected Papers.

#	Screening Criteria
1	Conceptual paper
2	Paper describes the model without any evaluation
3	Online learning is described in the article but has no substance and connection to machine learning
4	Short paper, research in progress or extended abstract

Based on the three stages involved in the selection of articles employed in this study, a few papers have been generated, comprising of:

Table 5: Result Criteria for Excluded Paper

Digital Libraries	Total Result
Emerald	6 Article
IEEE	3 Article
Science Direct	11 Article
Springer	7 Article
World of Science	2 Article

4. RESULT AND DISCUSSION

4.1 Research Purposes

Researchers encounter several goals and challenges when it comes to the implementation of machine learning in the field of education. The research and research problems associated with applying machine learning in learning are presented in Table 6 below.

Table 6: Research Purposes.

#	Research Purposes	Article by
1	predict students' grades and performance	[18][19][20][21][22][23][12][24][25][11] [26][27][28]
2	predict student at risk of academic failure	[29][30][31][32][33][34]
3	predict student drop out	[35][36][37]
4	predict learner preference	[38][39] [40] [41]
5	to detect dishonest students	[42]
6	suggesting remedial actions	[43]
7	predict student answer	[44]
8	predict student satisfaction	[45]

As depicted in the table above, the most prevalent issue that arises is the prediction of student grades and performance. Additionally, researchers have also identified the need to predict students who are at risk of academic failure as another significant concern.

4.2 Model and Approaches

To address the research problems at hand, researchers employ various models and approaches. Table 7 provides an overview of the models and approaches utilized by these researchers.

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Table 7: Model and Approaches.

#	Models and Approaches	Article by
1	Supervised machine learning	[18][43][19][20][21][29][31][39][44][40][23][12][24][25][37][11][45]
2	Learning analytic	[42][36][27][28][33][34]
3	Deep learning	[35][38][41]
4	Educational Data Mining Technique	[22]
5	Exploratory Data Analytics (EDA)	[26]
6	Sentiment Analysis	[45]

As portrayed in Table 7, supervised machine learning emerges as the most widely utilized model and approach. Moreover, researchers also leverage a multitude of learning analytic approaches to analyze the challenges that arise in the context of online learning.

4.3 Feature

As a means of measurement, researchers utilize a diverse range of features obtained through machine learning algorithms. Table 8 showcases the features that researchers commonly employ.

Table 8: Features.

#	Feature	Article by
1	Multiple attributes	[18][43][20][29][22][35][36][38][31][26][23][12][24] [33][37][34][11][45]
2	Previous Performance	[19][27]
3	Study Duration	[19]
4	Forum	[21]
5	LMS Activities	[39][44]
6	Academic Profiles	[39]
7	Reading Record	[44]

As illustrated in Table 8, multiple attributes are the widely utilized features that undergo processing using machine learning algorithms.

4.4 Algorithm

Researchers have at their disposal an array of algorithms that can be employed to process data derived from online learning outcomes. Table 9 displays the algorithms that are widely adopted by researchers in mapping online learning outcomes using machine learning.

Table 9: Algorithm.

#	Algorithm	Article by
1	Decision Tree	[18][43][19][20][21][29][35][36][39][44][40][23][24]
2	Random Forest	[18][43][19][20][21][29][22][35][31][26][39][44][40][23][37][11]
3	Naive Bayes	[18][20][22][31][26][39]
4	K-Nearest Neighbors	[18][20][29] [22][35][31][26]
5	Logistic regression	[43][19][21][22][44][40][25][11]
6	Support vector machine	[43][19][21][29][35][31][26][23]
7	Learning analytic algorithm	[42]
8	Deep Learning	[35][38][28]
9	Artificial Neural Network	[31][23][12]
10	Gradient Boosting Machine	[31][44][40][34][45]
11	XGBoost	[44][37]
12	Recursive Feature Algorithm	[31]
13	Linear Discriminant Analysis	[26]
14	Regression Algorithm	[27]
15	Convolutional Neural Networks (CNNs)	[41]
16	Long Short-Term	[41]

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	Memory (LSTM)	
17	Adaptive Synthetic Algorithm (ADASYN)	[33]
18	Feed-Forward Neural Network	[37]

As indicated in Table 9, the Decision Tree and Random Forest algorithms are the most frequently employed algorithms for this purpose.

4.5 Evaluation Metric

A variety of evaluation metrics exist to assess and measure the outcomes of machine learning algorithm processing. Table 10 highlights the evaluation metrics that researchers commonly utilize.

Table 10: Evaluation Metric.

#	Evaluation Metric	Article by
1	Accuracy	[18][43][19][20][29][22][35][26][44][40][12][41][24][28][33][37][11]
2	F1-score/F-Measure	[43][19][21][29][35][39][44][12][41][24][28][37]
3	Precision	[43][19][21][29][39][44][23][12][24][28][37]
4	Recall	[43][19][21][29][35][38][39][44][24][28][37]
5	AUC	[35][31][33][37][34]
6	ROC curve	[19][34]
7	10-folds cross-validation	[19][31]
8	Distance metric	[42]
9	MAE	[27][45]
10	Mean Squared Error	[41][45]
11	Correlation Coefficient	[27]
12	K-Fold Cross Validation	[11]

As presented in Table 10, Accuracy, F1 Score, Precision, and Recall are the evaluation metrics most employed by researchers to evaluate the results of data processing using machine learning algorithms.

4.6 Finding (Optimal Algorithm)

By analyzing the outcomes of data processing using machine learning, researchers can identify the most effective algorithm in achieving their research objectives. Table 11 showcases the optimal algorithm identified in the researchers' studies.

Table 11: Optimal Algorithm.

#	Best Algorithm	Article by
1	Random Forest	[18][20][22][39]
2	Deep Learning Algorithm	[35][38]
3	Multiple Algorithm	[31][37]
4	Support Vector Machine	[26]
5	Regression Algorithm	[27]
6	Gradient Boosting Machine	[44][40][45]
7	XGBoost	[44]
8	Artificial Neural Network	[23][12]
9	Decision Tree	[24]

As depicted in Table 11, Random Forest emerges as the algorithm that appears most frequently and is considered to have the highest evaluation value by researchers.

4.7 Designing a Machine Learning Model to Attain Specific Skills

Designing a Machine Learning Model to Attain Specific Skills Drawing upon the results of the literature review discussed above, Table 12 exemplifies the application of learning elements, indicators, algorithms, and evaluation metrics primarily used to map the attainment of specific skills. This example also addresses research question number 2.

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The findings of this research are consistent with recommendations of previous research by [46] who stated that further research is needed in order to formalise a specific definition of learning outcomes before attempting to develop predictive models that measure learning outcomes achievement.

5. OPEN RESEARCH ISSUES

There exist unresolved research matters that can be emphasized from the utilization of machine learning in the sphere of applying machine learning models in online learning, which can subsequently be employed to attain skills.

5.1 Machine Learning Approach in a Learning Management System (LMS)

To furnish students with precise and pertinent recommendations, it is imperative that ML algorithms are appropriately calibrated. Inaccurate or prejudiced recommendations may result from inadequate data quality or bias in the training data. The process of collecting and processing data and testing the model requires substantial effort to ensure its dependability.

Furthermore, the adoption of technology and the training of personnel present significant obstacles. Numerous educational institutions may lack the necessary technical expertise in ML, necessitating substantial resources to develop and maintain ML systems within an LMS. Additionally, effectively engaging lecturers, instructors, and students in the proficient use of an ML-enabled LMS requires efforts in training and comprehending this technology. Hence, comprehending and surmounting these challenges is vital in implementing ML in LMS to enhance the learning experiences of students.

5.2 Determining learning components, indicators, and algorithms in mapping student skill attainment

Mapping student skill attainment by means of learning components, indicators, and algorithms poses a formidable undertaking. Primarily, one of the main challenges lies in designing appropriate and effective learning components for each skill to be acquired. This encompasses the development of relevant materials, high-quality learning resources, and teaching methodologies that foster student motivation. Additionally, accurately measuring student progress through suitable indicators is also a challenge, as it must accurately reflect genuine development in these skills.

Secondly, the selection of an algorithm to map skill attainment is equally significant, particularly within the context of online learning and automation. Algorithms must aptly discern skill development, minimize errors, and possess reliability. Furthermore, ensuring that the algorithm can adapt to individual student proficiency levels is a critical aspect of implementing personalized and effective learning.

Lastly, determining appropriate evaluation metrics to gauge skill attainment can prove to be challenging. These metrics ought to illustrate progress clearly and accurately, allowing teachers, students, and parents to better comprehend skill development. Furthermore, they should encompass various facets of skills, including understanding concepts, applying them in real-life scenarios, and exhibiting initiative. By addressing these challenges, educators can more effectively map and enhance students' skills.

5.3 Evaluation of the Application of Machine Learning in Online Learning

The evaluation of the application of Machine Learning in online learning confronts several challenges that necessitate resolution. Firstly, issues of accuracy and bias come into play. Machine Learning models may exhibit reduced accuracy when utilized in online learning contexts due to the heterogeneous and diverse nature of student data. Additionally, bias in the training data can manifest in recommendations and assessments, influencing students' learning experiences in an unjust manner. Hence, it is crucial to continually develop evaluation techniques that can identify and overcome bias while maintaining model accuracy.

Secondly, the evaluation of the application of Machine Learning in online learning encounters the challenge of scalability. As the number of students and the amount of data to be processed increases, it becomes imperative to have a robust and scalable infrastructure in place to execute Machine Learning

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models efficiently. This challenge is closely linked to the issue of data security, as accessing, and processing a larger volume of student data heightens the risk of data leaks and privacy breaches.

Lastly, the evaluation process involves grappling with the understanding and interpretation of the model itself. Machine Learning models often possess intricacies, making it arduous for users to comprehend the reasoning behind the recommendations or decisions made by the model. Consequently, it becomes crucial to develop tools and methodologies that empower users, including educators and students, to grasp the fundamental workings of the model. This entails comprehending the factors that influence the recommendations or assessments provided by the system. By surmounting these challenges, the evaluation of the application of Machine Learning in online learning can achieve greater transparency, fairness, and effectiveness.

5.4 Potensial Threats to Validity

1) This research includes digital lectures from various online databases. Therefore, some important papers might be missed, either because they are poorly indexed in these databases or because they are not indexed in alternative digital libraries.
2) The literature review may exhibit bias by favouring studies published in reputable journals, potentially neglecting unpublished or less prominent studies, and resulting in a distorted view of the research landscape.
3) The article should present a balanced view of the benefits and drawbacks of machine learning in education. It should avoid highlighting only studies that support the benefits of machine learning while neglecting contradictory evidence or studies that raise concerns about its implementation in online learning.

5.5 Suggestions for Future Research

Given the challenges and limitations outlined above, we propose the following research recommendations for achieving proficiency in online learning:

Recommendation (1): To improve the overall educational experience, the focus should be on overcoming the challenges associated with adopting technology and increasing engagement with machine learning capabilities.

Recommendation (2): Future research could look at the creation of appropriate materials, of high-quality learning resources and of teaching methods that promote the motivation of students. It will also explore the selection of precise indicators that accurately reflect real skill development.

Recommendation (3): Investigate the effectiveness of machine learning applications in different cultural and educational settings. Analyse how cultural differences affect the performance and outcomes of machine learning in online learning environments.

6. CONCLUSION

This systematic review of the literature examines the utilization of Machine Learning (ML) in online learning, specifically focusing on skill acquisition. This comprehensive analysis encompasses a range of studies conducted in this field. The findings of this research demonstrate that ML plays a significant role in enhancing the online learning experience, offering considerable potential for improving students' skill acquisition. Various ML techniques, including classifiers, regression, and clustering, are employed to identify patterns that can facilitate personalized curriculum development and individual progress assessment. ML can be utilized in the online learning process to analyze learning data, identify potential obstacles faced by students, and provide appropriate recommendations to overcome these challenges.

Moreover, this literature review also underscores the challenges and difficulties encountered when using ML in the context of online learning. Issues related to data privacy, the scarcity of high-quality data, and technical obstacles in implementing ML algorithms often hinder the integration of ML in online learning. Consequently, collaboration among researchers, practitioners, and technology developers is crucial to surmount these obstacles.

The conclusions drawn from this literature review contribute to a deeper understanding of the impact of ML on online learning and students' skill acquisition. The findings indicate that ML has substantial potential to revolutionize the online learning process by enabling enhanced personalization, more accurate progress assessment, and more relevant recommendations for students. Nevertheless, it is imperative to overcome the existing challenges and ensure that the utilization of ML in online learning yields maximum benefits. Through effective collaboration among various stakeholders, ML can serve as a valuable tool in enhancing the quality of online education and achieving superior skill acquisition.

Future research in the field of employing Machine Learning in online learning should prioritize the development of more advanced and efficient models to gain a deeper understanding of student learning behavior. Additionally, research endeavors should explore methods to overcome data privacy constraints by incorporating robust security techniques in the application of ML in online learning contexts. Moreover, it is essential to conduct further empirical research to evaluate the effectiveness of ML in enhancing students' skill acquisition and overall learning outcomes. Lastly, research should also consider the ethical implications associated with the utilization of ML in the realm of online education and establish clear guidelines for safeguarding the security and privacy of student data.

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Table 12: Machine Learning Model Design.

KKNI Competency Unit	Assessment Context	Model and Approaches	Algorithm	Feature	Evaluation Metric
Designing the user experience	Study Case	Supervised machine learning[18][43] [21] [39][44]	Decision Tree, Random Forest[18][43] [21] [39][44]	Multiple attributes[18][43][36]	Accuracy, Precision, Recall, F-1 Score[18][43] [21] [39][44]
Design application architecture	Hands-On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]
Implement problem solving into subroutines	Hands-On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]
Implement structured programming	Hands-On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]
Implements object-oriented programming	Hands-On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]
Implement programming algorithms	Study Case	Supervised machine learning[18][43] [21] [39][44]	Decision Tree, Random Forest[18][43] [21] [39][44]	Multiple attributes[18][43][36]	Accuracy, Precision, Recall, F-1 Score[18][43] [21] [39][44]
Create program code documents	Hands-On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]
Migrating to new technology	Study Case	Supervised machine learning[18][43] [21] [39][44]	Decision Tree, Random Forest[18][43] [21] [39][44]	Multiple attributes[18][43][36]	Accuracy, Precision, Recall, F-1 Score[18][43] [21] [39][44]
Debugging	Study Case	Supervised machine learning[18][43] [21] [39][44]	Decision Tree, Random Forest[18][43] [21] [39][44]	Multiple attributes[18][43][36]	Accuracy, Precision, Recall, F-1 Score[18][43] [21] [39][44]
Perform program profiling	Hands On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]

			Machine[36][27] [34]		
Provide technical instructions to customers	Study Case	Supervised machine learning[18][43] [21] [39][44]	Decision Tree, Random Forest[18][43] [21] [39][44]	Multiple attributes[18][43][36]	Accuracy, Precision, Recall, F-1 Score[18][43] [21] [39][44]
Execute application cutover	Hands On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]
Carry out software configuration according to the environment (development, staging, production)	Hands On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]
Implement an alert notification if the application has a problem	Hands On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]
Perform software updates	Hands On	Learning analytic[36][27] [34]	Decision Tree, Regression Algorithm, Gradient Boost Machine[36][27] [34]	Multiple attributes[18][43][36]	Accuracy, ROC, MAE[36][27] [34]