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A Systematic Review of Machine Learning Techniques for Smart Governance in Higher Education

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Abstract **Review Article**

This study presents a systematic literature review (SLR) of machine learning (ML) applications in higher education governance, addressing the growing need for smart governance frameworks in academic institutions. While ML has seen widespread adoption in sectors like finance and healthcare, its integration into higher education remains fragmented. This review began with an initial review of twenty relevant papers to establish thematic baselines, followed by a systematic screening of over 1,100 records using the PRISMA 2020 methodology. From these, 29 studies were selected for in-depth analysis. The review identifies key trends in ML algorithm usage, evaluation metrics, and application domains—ranging from student performance prediction to strategic planning and faculty assessment. Findings reveal critical gaps in empirical validation, scalability, ethical considerations, and real-world implementation, particularly in low- and middle-income countries. The study highlights emerging opportunities in decentralized governance, MLOps, and explainable AI, and proposes a roadmap for building scalable, context-aware, and ethically grounded ML-driven governance models for academia.

Keywords: Smart Governance, Higher Education Institutions (HEIs), Machine Learning (ML), Institutional Management.

1.0 INTRODUCTION

The convergence of digital transformation and data-intensive environments has propelled the concept of smart governance into the mainstream of public and institutional discourse. Rooted in the broader philosophy of e-governance, smart governance refers to the use of advanced digital technologies—including artificial intelligence (AI), machine learning (ML), and data analytics—to optimize decision-making, improve service delivery, and foster participatory management in both governmental and non-governmental contexts. While smart governance has been extensively explored in domains such as public sector innovation, smart cities, and financial regulation, its application within the governance frameworks of higher education institutions (HEIs) remains emergent, fragmented, and under-researched.

At the same time, the rapid digitalization of the education sector has intensified interest in deploying ML techniques to support and enhance governance mechanisms in HEIs. As the scale and complexity of academic operations grow, traditional decision-making methods are proving increasingly inadequate for managing dynamic institutional demands (Swiontek et al., 2019; Nieto et al., 2019). Machine learning, with its capacity for predictive, automated, and data-driven insights, holds transformative potential across a wide range of administrative and academic functions. These include predictive analytics for student outcomes, faculty evaluation, strategic planning, curriculum design, resource allocation, and institutional performance forecasting (Pinto et al., 2023; Deng, 2024).

Despite these possibilities, HEIs—though inherently data-rich and innovation-driven—have been slower to adopt ML-powered smart governance systems compared to sectors like finance, healthcare, and public administration. This gap underscores a compelling need to systematically examine the scope, limitations, and potential of ML applications in academic institutional management. While certain models have demonstrated localized success, such implementations remain the exception rather than the norm.

Academic institutions generate vast volumes of both structured and unstructured data—ranging from student performance records and infrastructure usage logs to faculty feedback and administrative workflows. Yet, as studies reveal, the deployment of ML to manage, analyze, and extract actionable insights from such data has not matured into a standardized or strategic practice across institutions (Balcerzak et al., 2022). While blockchain and ML have shown promise in enhancing transparency in urban governance, similar integrative models remain underdeveloped within academia. This technological underutilization suggests a missed opportunity to build more responsive, adaptive, and data-literate educational systems.

Current literature indicates that most applications of ML in education are confined to operational and tactical tasks, particularly those related to predictive analytics. For instance, Mary Mwangi (2024) employed ML models such as Random Forest, LSTM, and Gradient Boosting Machines (GBM) to assess financial risk in education funding. Similarly, Talha Mahboob Alam et al. (2021) used ensemble algorithms to predict school performance and highlight rural-urban disparities. Other studies demonstrate strong algorithmic performance in graduation rate forecasting, identifying at-risk students, and optimizing academic feedback systems (Barnes et al., 2024; Nauman et al., 2021). These efforts point to a growing reliance on supervised learning and classification models—such as decision trees, support vector machines (SVMs), and deep neural networks—in student-centric use cases.

Other studies demonstrate strong algorithmic performance in graduation rate forecasting, identifying at-risk students, and optimizing academic feedback systems (Barnes et al., 2024; Nauman et al., 2021). Otu et al. (2024) further showed that supervised learning models like logistic regression and random forests achieved high accuracy (up to 93%) in predicting academic outcomes, reinforcing the value of ML in student-centric governance use cases.

Encouragingly, some initiatives have extended ML to high-level governance functions, including academic scheduling, budget forecasting, and institutional resource optimization (Siram et al., 2024; Villegas-Ch. et al., 2023). These signal a broader transition from operational analytics to strategic intelligence. Frameworks that integrate ML with administrative dashboards and learning management systems have shown promise in fostering institutional agility, innovation, and excellence. Nonetheless, such frameworks are often isolated and lack mechanisms for benchmarking, replication, or scalability.

Compounding these implementation gaps is a fragmented research landscape. A systematic literature review of 1,887 Scopus-indexed publications found that only 171 articles met inclusion criteria for exploring ML in higher education—and most of those focused narrowly on student performance prediction (Pinto et al., 2023). Another review by Deng (2024) identified just 11 articles addressing ML in curriculum and institutional design, with only three peer-reviewed. These findings illustrate the underrepresentation of institutional-level ML adoption in both academic research and governance practice, as well as a lack of methodological robustness and comprehensive evaluations.

Empirical evidence further highlights persistent systemic challenges within academic governance. For example, Wang et al. (2021) reported that university governance in China is hindered by ambiguous power structures and underdeveloped communication systems—barriers that could be alleviated through intelligent systems, yet actual implementations remain scarce. Likewise, Hidayat and Sensuse (2022) developed a knowledge management model for Indonesian smart campuses, but found no integration of predictive or adaptive ML features, underscoring the fragmented and nascent nature of digital governance strategies in HEIs.

Where ML implementations do exist, they tend to be localized, unstandardized, and lacking in scalability. Siram et al. (2024), for instance, developed a performance management model based on a Multilayer Perceptron (MLP) algorithm with a promising R^2 score of 0.842, but this approach has yet to gain broader traction or be validated across different institutional contexts. Similarly, Nieto et al. (2019) demonstrated that ML could optimize graduation forecasting, admissions planning, and resource management, but noted that many HEIs still rely on semi-automated or manual systems.

Global disparities in ML adoption further complicate the landscape. Studies from sub-Saharan Africa highlight ML's potential to address long-standing issues such as high faculty-to-student ratios, infrastructural limitations, and data fragmentation (Fomunyam, 2020). However, such projects are often pilot-based, underfunded, and misaligned with institutional policy frameworks. The work by Yakubu and Abubakar (2021) in Nigeria, for example, offered insights into student performance analytics but lacked algorithmic benchmarking and generalizability. Such projects are often pilot-based, underfunded, and misaligned with institutional policy frameworks (Lawal, Ibrahim, & Mohammed, 2021).

Moreover, the ethical, technical, and operational dimensions of ML adoption in academic governance remain unresolved. Varde (2025), in her analysis of ML for urban governance, emphasized the importance of long-term algorithmic fairness and explainability—concerns magnified in educational settings where decisions affect admissions, evaluations, and funding. Zongyu Sun (2025) further showed that while convolutional neural networks (CNNs) improved human resource performance prediction, the reliance on small datasets and absence of validation mechanisms raises scalability and bias concerns—issues equally applicable to academia.

The broader implications of ML for academic governance thus extend beyond efficiency gains to include deeper questions about autonomy, accountability, fairness, and institutional ethics. For instance, Ruishu Wang et al. (2021) found that while intelligent decision systems in Chinese universities improved internal communication and autonomy, they frequently lacked transparency and empirical rigor. Similarly, Z.R.M. Abdullah Kaiser (2024) emphasized the need for stakeholder-informed governance frameworks that align with local socio-political realities, especially in developing countries where digital literacy levels vary significantly.

Altogether, the current state of ML adoption in higher education governance reveals both promise and fragmentation. The diversity of algorithms, implementation strategies, and institutional contexts reflects a rich but inconsistent landscape, one that lacks a consolidated framework for benchmarking, scaling, and ethical deployment. As institutions face increasing complexity due to digital transformation and data proliferation, there is a clear need for technically sound, ethically grounded, and adaptable smart governance strategies.

This study therefore aims to address these gaps by conducting a systematic review of ML applications in academic governance, with particular emphasis on successful models, underexplored challenges, and policy-aligned pathways for broader institutional integration. By synthesizing and evaluating existing literature across methodological and contextual dimensions, the study offers a critical reference point for academics, policymakers, and technology leaders seeking to modernize and future-proof governance practices in higher education.

1.1 Objectives of the Study

i. Systematically identify and classify the machine learning algorithms (e.g., supervised, unsupervised, reinforcement learning, ensemble methods) utilized in higher education governance, along with their technical configurations and implementation settings.

ii. Map the functional domains of institutional governance where ML has been applied—such as strategic planning, admissions management, academic performance monitoring, budget forecasting, faculty evaluation, and policy compliance.

iii. Assess the reported effectiveness, accuracy, and impact of ML applications on institutional decision-making processes, including predictive accuracy (e.g., R^2, precision, F1-score), scalability, and integration with existing administrative systems.

iv. Examine regional and contextual disparities in ML adoption across high-income and low- to middle-income countries (LMICs), with a focus on infrastructure readiness, stakeholder engagement, and policy alignment.

v. Identify conceptual and methodological gaps in the existing literature related to ethics, algorithmic fairness, explainability, and governance transparency in ML deployment within HEIs.

2.0 REVIEW OF RELEVANT LITERATURE

The recent proliferation of machine learning (ML) technologies across sectors such as finance, healthcare, and urban planning has gradually extended to higher education, where data-intensive environments and growing administrative complexity present both challenges and opportunities for innovation. While the technical capabilities of ML are well-established, their adaptation to the nuanced, hierarchical, and often bureaucratic structure of academic institutions poses unique constraints. Nonetheless, interest in ML-enabled smart governance frameworks for education is rapidly growing, driven by the need for data-driven institutional planning, performance optimization, and improved stakeholder engagement.

1. Overview of ML in Higher Education Governance

A growing body of research reflects this shift. A systematic review of 1,887 Scopus-indexed publications revealed that only 171 studies specifically addressed ML applications in higher education, with the majority focusing on student performance prediction rather than broader aspects of institutional governance (Pinto et al., 2023). Similarly, Deng (2024) identified just 11 studies related to ML in curriculum and institutional design, of which only three were peer-reviewed. This indicates a critical research gap in applying ML tools to domains like administrative decision-making, policy enforcement, and institutional performance forecasting.

Despite these limitations, several empirical studies highlight the potential of ML for improving academic governance structures. Siram et al. (2024) employed ML models—including Multilayer Perceptrons (MLP), Decision Trees, and Random Forests—to predict institutional performance metrics such as student success and faculty productivity. MLP models achieved an R^2 score of 0.842, demonstrating strong predictive capacity. Likewise, Nieto et al. (2019) used ML to enhance decision-making for graduation forecasting and academic planning, with Random Forests providing the most accurate results.

2. Applications in Institutional Strategy, Performance, and Faculty Evaluation

The utility of ML in institutional strategy extends beyond student analytics. Alam et al. (2021) tested several models—including ANN, SVM, and Random Forest—to forecast school performance in Pakistan, finding ANN to be the most robust for educational prediction. However, they emphasized the need for context-specific generalizability, as many models fail to transfer effectively across national education systems.

Similarly, Yakubu and Abubakar (2021) used logistic regression to identify socio-demographic predictors of academic performance at a Nigerian university, revealing key variables such as gender and regional background. Although insightful, the study's scope was limited to a single institution, reinforcing the demand for scalable governance models.

ML has also been utilized in faculty evaluation processes. One study (No author, 2019) compared the accuracy of SVM, Logistic Regression, and Random Forest models in analyzing student feedback to evaluate teaching performance. Random Forests yielded the best outcomes, with 73.1% accuracy and a 78.7% F1-score, indicating ML's potential in automating and refining administrative feedback loops.

3. Technical Foundations of ML-Driven Governance

Recent contributions have extended into the technical methodologies underpinning ML governance in education. These include data analytics, decentralized infrastructures, MLOps integration, and blockchain-enabled frameworks.

Data Analytics and Machine Learning Algorithms

ML-based decision systems typically involve stages such as data preprocessing, feature extraction, model training, and validation. These steps support applications like automated grading through NLP, predictive academic modeling, and institutional diagnostics. For instance, NLP-based essay scoring systems leverage deep learning and clustering to assess open-ended responses, offering scalable and objective feedback mechanisms.

Decentralized Governance and Blockchain Integration

Decentralization introduces new layers of transparency and equity. Balcerzak et al. (2022) proposed blockchain-integrated frameworks for smart governance, emphasizing spatial computing and reinforcement learning. In higher education, such systems can enable secure academic recordkeeping, decentralized identity management, and community-driven decision-making through smart contracts and DAOs (Decentralized Autonomous Organizations). This approach minimizes reliance on centralized authority and enhances trust in automated governance processes.

MLOps in Governance Systems

MLOps—the fusion of machine learning with DevOps principles—facilitates continuous model deployment, scalability, and automated monitoring. Applied to academia, it supports the dynamic evolution of institutional policies and workflows. Features like CI/CD pipelines, automated anomaly detection, and real-time governance dashboards enhance adaptability and system resilience.

2.1 Technical Summary Table

Table 1: Technical Components in ML-Driven Governance Frameworks

Technical Component	Description	Implementation Example
Data Analytics & NLP	Analysis of textual and numerical datasets	Automated grading; student diagnostics
Blockchain Integration	Transparent, decentralized record-keeping	Smart contracts for funding and asset tracking

Decentralized Decision-Making	Stakeholder-led policy changes via smart contracts	DAO-based frameworks for governance votes
MLOps	Automated deployment and monitoring of ML systems	Real-time scheduling, policy updates, CI/CD for models

Conceptual Models and Governance Frameworks

Beyond applications, conceptual models provide critical scaffolding for implementing ML in governance. Veale and Brass (2019) introduced a macro–meso–micro institutional lens, helping to map how ML functions across policy, operational, and algorithmic layers. Although not education-specific, their model offers a blueprint for integrating ML into academic governance systems.

Similarly, Hidayat and Sensuse (2022) developed a five-layer knowledge management (KM) model for Indonesian universities that included infrastructure, human capital, and organizational learning. While their framework lacked real-time ML capabilities, it highlighted the importance of institutional capacity-building in smart campus initiatives.

Ethical, Cultural, and Stakeholder Considerations

As with any governance reform, ethical and stakeholder concerns must be central. Kaiser (2024) emphasized the importance of stakeholder-driven governance models that are culturally sensitive—especially in developing nations. Lutz and Newlands (2021) proposed a trustworthiness framework to assess public acceptance of AI systems, with implications for transparency and fairness in university contexts.

Varde (2025) further demonstrated that explainable AI models like Decision Trees and Naive Bayes can promote equity in algorithmic decision-making. Her urban governance study, although not education-specific, illustrates how interpretability and inclusivity in algorithm design can build user confidence—a necessary condition for institutional adoption in academia.

Regional Challenges and Equity Concerns

ML adoption in education is not uniform. In sub-Saharan Africa, for instance, Fomunyam (2020) advocated for ML-based solutions to problems such as infrastructure deficits and high dropout rates. However, Gardner et al. (2023) cautioned against uncritical adoption of ML models across diverse educational systems, emphasizing the need for fairness, contextual fit, and cross-cultural adaptability in governance technologies.

2.2 Summary of Gaps and Opportunities

Taken together, the literature reveals a multi-directional yet fragmented landscape of ML research in higher education governance. While predictive models and technical frameworks are evolving, most efforts remain narrowly focused or lack systemic implementation strategies. Moreover, ethical governance, stakeholder involvement, and scalability across diverse regions are still underexplored. This underscores the necessity of a systematic review to consolidate existing research, evaluate methodological diversity, and guide future innovations toward equitable, scalable, and transparent smart governance in academia.

3.0 METHODOLOGY

As shown in Table 2, This study adopted a Systematic Literature Review (SLR) methodology, adhering to the PRISMA 2020 framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to ensure transparency, methodological rigor, and replicability throughout all phases of the review.

1. Data Sources

The review incorporated peer-reviewed journal articles, conference proceedings, and prior systematic reviews published in English. A wide range of academic databases were searched to ensure comprehensive coverage:

i. Scopus
ii. IEEE Xplore
iii. ScienceDirect
iv. Web of Science
v. ERIC (Education Resources Information Center)
vi. Education Research Complete
vii. Google Scholar (filtered for scholarly relevance)

2. Search Strategy

A structured search strategy using both controlled vocabulary and free-text keywords was developed and iteratively refined. Boolean operators and truncation symbols were applied to optimize retrieval.

Sample search phrases included:
"machine learning" AND "higher education"
"institutional governance" OR "academic management"
"smart campus" AND "decision-making"
"predictive analytics" AND "university planning"

A search string matrix was constructed to combine terms across domains (e.g., [Technology] × [Governance] × [Education]).

3. Inclusion Criteria

Studies were included if they:

a) Were published between 2018 and 2024
b) Were written in English
c) Applied ML techniques in the context of higher education governance or management
d) Provided empirical results or proposed frameworks/models
e) Had accessible full-text versions

4. Exclusion Criteria

Exclusion was applied to studies that:

a) Focused solely on student learning or pedagogy
b) Did not involve machine learning methods
c) Were not peer-reviewed or published in English
d) Were duplicates or of poor academic quality

5. Screening and Selection Procedure

Figure 1 illustrates the selection process followed using PRISMA 2020 flow (Page et al., 2021), conducted in three stages—title screening, abstract screening, and full-text review—by two independent reviewers. Discrepancies were resolved through discussion or third-party adjudication.

i. Records identified: 1,120
ii. Duplicates removed: 430
iii. Automated removals: (n = 123) were conducted using Rayyan's duplicate detection algorithm, which excluded records with identical metadata entries prior to manual screening. (The automated removals were performed using Rayyan QCRI, the systematic review platform. After importing the initially retrieved records into Rayyan, the software automatically identified and excluded 123 duplicate entries based on metadata (titles, authors, publication years, and DOI matching). Rayyan employs a built-in algorithm for rapid duplicate detection, which minimizes human error and accelerates the screening process.)
iv. Records screened: 567
v. Excluded at screening: 439
vi. Reports sought for retrieval: 128
vii. Not retrieved: 52
viii. Assessed for eligibility: 76
ix. Excluded after full-text review: 47
x. Studies included in synthesis: 29

Tools Used:

a. Rayyan QCRI for collaborative, blinded screening and tracking decisions (Ouzzani et al., 2016).

b. Zotero or EndNote for citation management and de-duplication.

c. Cohen's Kappa used for inter-rater reliability assessment

6. Data Extraction

A standardized form was developed (in Excel or NVivo) to extract key data points:
Author(s), year, location
ML algorithm type (e.g., SVM, RF, ANN)
Application domain (e.g., strategic planning, admissions)
Dataset attributes (e.g., sample size, region)
Evaluation metrics (accuracy, F1, etc.)
Outcomes, limitations, ethical concerns
Frameworks or models proposed

7. Data Analysis

A thematic synthesis was conducted using Braun & Clarke's six-phase framework for qualitative data analysis (Braun & Clarke, 2006). Descriptive statistics were used to quantify methodological trends where applicable.

Narrative synthesis and evidence gap mapping helped surface emerging themes, methodological gaps, and underrepresented areas in the literature.

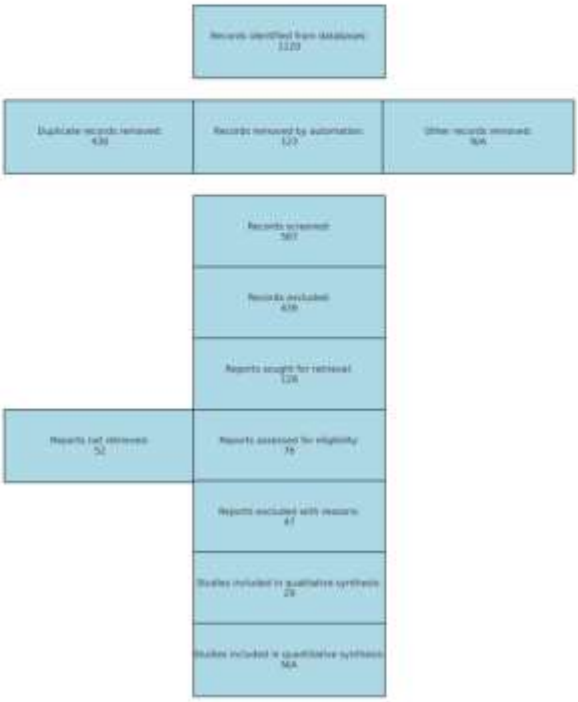

Figure 1: PRISMA 2020 flow diagram

4.0 DATA PRESENTATION AND ANALYSIS

This section presents the findings derived from the systematic literature review on the use of machine learning (ML) in institutional governance within higher education. Drawing from a curated set of 29 peer-reviewed studies, the analysis highlights patterns in algorithm usage, data characteristics, evaluation methods, and the functional domains of application. Particular attention is given to the frequency and effectiveness of various ML models, the diversity of datasets utilized, and the metrics employed to assess model performance.

Additionally, this section identifies critical research gaps and regional disparities in ML adoption, offering insights into both the progress made and the limitations that persist in the field. The results are structured thematically and supported by summary tables and figures to enhance interpretability and contextual understanding.

Key themes—including the types of ML algorithms used, datasets employed, evaluation metrics, research focus, and existing gaps—are comprehensively summarized in Table 2, 3 and 4.

4.1 Systematic Literature Review Table

4.1.1 Empirical Applications of Machine Learning in Higher Education Governance

Table 2 presents studies where machine learning (ML) algorithms were applied to specific datasets, accompanied by evaluation metrics. These studies demonstrate real-world or pilot applications of ML techniques in academic settings, offering empirical evidence of their effectiveness.

Table 2: Empirical Studies with ML Applications

Author(s)	Year	ML Algorithm(s)	Dataset Used	Evaluation Metric(s)	Application Area
Meiling Lu	2025	LSTM, DQN	Simulated environments	Decision success probability	Automated decision-making
Zongyu Sun	2025	CNN + Learning Automata	Custom HR dataset	Accuracy, Precision, AUC	HR performance analytics
Mary Mwangi	2024	RF, SVM, GBM, Logistic Regression, etc.	Financial datasets	Accuracy, fraud detection	Financial risk management
Aurelia Regina de Andrade	2023	SVM, Decision Trees, Naive Bayes, etc.	Gov audit reports	Precision, F1, Accuracy	Government transparency
Jozsef Pap et al.	2022	GA, BART	European Company Survey	MAE, MSE, RMSE	Organizational outcomes modeling
Olivia Muiruri, Agnes Njeru	2022	Association Rule Mining, Classification	Kenyan firms	Classification accuracy	Project governance
Omar Salazar et al.	2022	Decision Trees, SVM, ANN	Chilean government employees	Accuracy, F1 Score	HR planning in public sector
Talha Mahboob Alam et al.	2021	J48, SVM, RF, Rotation Forest, ANN	High school data, Pakistan	Accuracy, F1-score	School performance prediction
Mohammed Nasiru Yakubu, Abubakar	2021	Logistic Regression	Student records, Nigeria	Accuracy, Odds Ratios	Student performance prediction
Yash Raj Shrestha et al.	2021	CNN, MLP, BERT, etc.	Fashion-MNIST,	Accuracy, Precision, Recall	Organizational decision-making

			Rotten Tomatoes		
Luminita Hurbean et al.	2021	LSTM, CNN, ANN, etc.	Smart city datasets	Accuracy, F1, RMSE	Smart city development
Zhigang Zhou et al.	2020	ML-AR, Apriori, OBDM	UCI datasets	Support sensitivity, PCA	Knowledge management enhancement
Almeida et al.	2020	Text Classification, Decision Trees, etc.	Brazilian procurement data	Accuracy, Precision, Recall	Anti-corruption systems
L. Jason Anastasopoulos & Andrew B. Whitford	2018	GBT	Federal agencies' tweets	Accuracy, Precision	Public sector communication

4.1.2 Conceptual and Theoretical Contributions

Table 3 summarizes conceptual and theoretical contributions that explore machine learning (ML) and governance without empirical implementation. These papers provide critical strategic, ethical, and theoretical perspectives that can guide future empirical research.

Table 3: Conceptual and Non-Empirical Studies

Author(s)	Year	Focus Area
Aparna S. Varde	2025	AI for inclusive policy
Bas Geerdink	2024	ML adoption strategy in finance
Z.R.M. Abdullah Kaiser	2024	Smart governance policies
Adam P. Balcerzak et al.	2022	Blockchain and ML governance
Deden Sumirat Hidayat, Dana Indra Sensuse	2022	Smart campuses knowledge management
Vijayakumar Thota, Gunda Srinivas	2022	ML in Education 4.0
Osama Al-Jarrah, Alex Koohang	2022	Big data governance
Ruishu Wang et al.	2021	AI in academic governance
Christoph Lutz, Gemma Newlands	2021	Trust in algorithmic governance
Elena Raviola, Johan Hagberg	2021	AI's organizational impact
Mauricio Solar et al.	2020	Public value theory and AI
Gianluca Misuraca et al.	2020	Strategic AI frameworks
Michael Veale, Irina Brass	2019	Automation vs augmentation systems
Rania Afiouni-Monla	2019	ML in organizational learning

4.1.3 Machine Learning Algorithm Categorization

Table 4 classifies the reviewed studies based on the type of machine learning (ML) technique applied—supervised learning, deep learning, reinforcement learning, hybrid models, or conceptual/theoretical works. This structure offers insight into technological focus areas and emerging trends.

Table 4: ML Algorithm Types Grouping

ML Type	Example Algorithms	Number of Studies
Conceptual/Theoretical	No algorithms applied	14
Supervised Learning	SVM, RF, Decision Trees, Logistic Regression, GBT	10
Deep Learning	CNN, LSTM, MLP, BERT	5
Hybrid/Ensemble	GBM, XGBoost, BART, Ensemble methods	4
Reinforcement Learning	DQN, Learning Automata	2

4.2 Results

This section outlines the key empirical patterns identified through the systematic literature review (SLR), offering a quantitative and thematic synthesis of trends in machine learning (ML) applications within higher education governance. The findings are organized across several critical dimensions: publication trends, types of ML algorithms used, evaluation metrics, data practices, research focus, and identified gaps.

Each aspect is presented using visual summaries (figures and tables) to enhance interpretability. Trends in algorithm popularity, reliance on specific datasets, and common evaluation practices are examined to assess the methodological robustness of existing studies. Furthermore, an analysis of research focus areas reveals a fragmented but growing interest in diverse governance functions. Finally, the section categorizes both addressed and unaddressed research gaps, emphasizing persistent limitations in scalability, ethical implementation, and real-world applicability. These findings collectively inform the foundation for the subsequent discussion and recommendations.

4.1.1 Publication Year

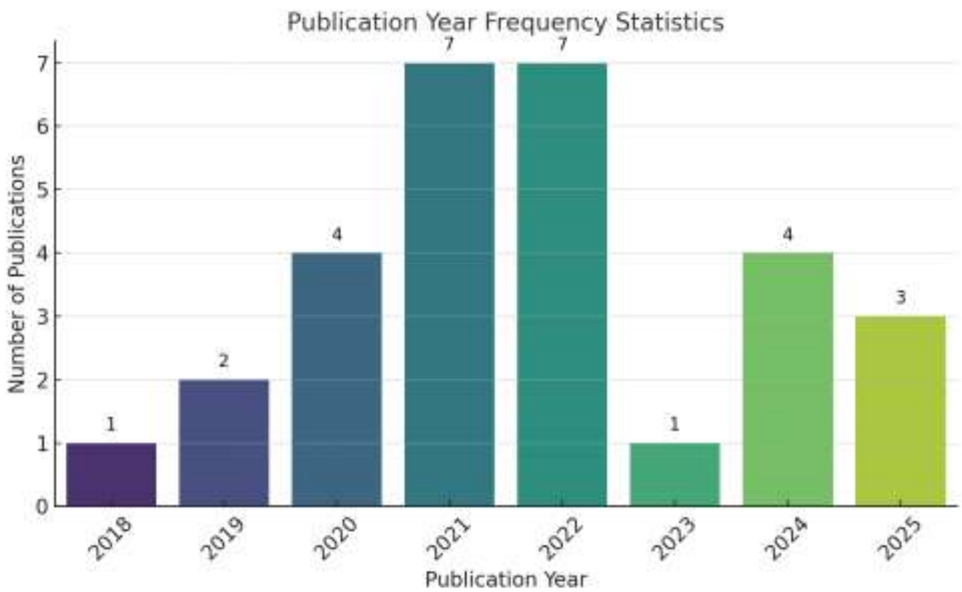

Figure 2: Publication Year of Reviewed Papers

Figure 2 illustrates a steady rise in publications from 2018 to 2022, peaking in 2021 and 2022. Although there was a slight decline in 2023, the number of publications rebounded in 2024 and 2025. This trend indicates that the majority of the reviewed papers were published from 2021 onward, highlighting the study's reliance on recent and up-to-date literature.

4.1.2 Machine Learning Algorithms

Figure 3 illustrates the top 10 machine learning algorithms used in studies related to smart governance in higher education, based on frequency. Support Vector Machine (SVM) is the most commonly applied algorithm, appearing in 8 papers. It is followed by Random Forest (RF) with 6 occurrences. A group of algorithms—Logistic Regression, Convolutional Neural Networks (CNN), Naive Bayes, Artificial Neural Networks (ANN), Decision Trees, and Long Short-Term Memory (LSTM)—are each cited 4 times. Deep Learning (DL), with just 2 mentions, ranks lowest among the top 10. Overall, SVM emerges as the preferred method, while other algorithms show a relatively balanced distribution.

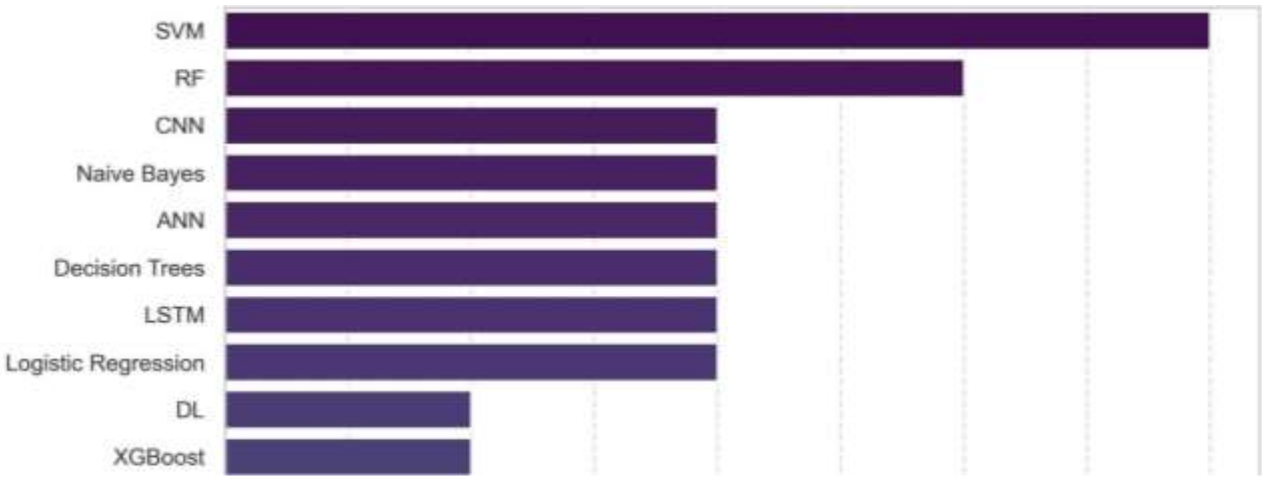

Figure 3: Top Ten MLAs Used Across Reviewed Papers

4.1.2.1 Distribution of ML Algorithm Types

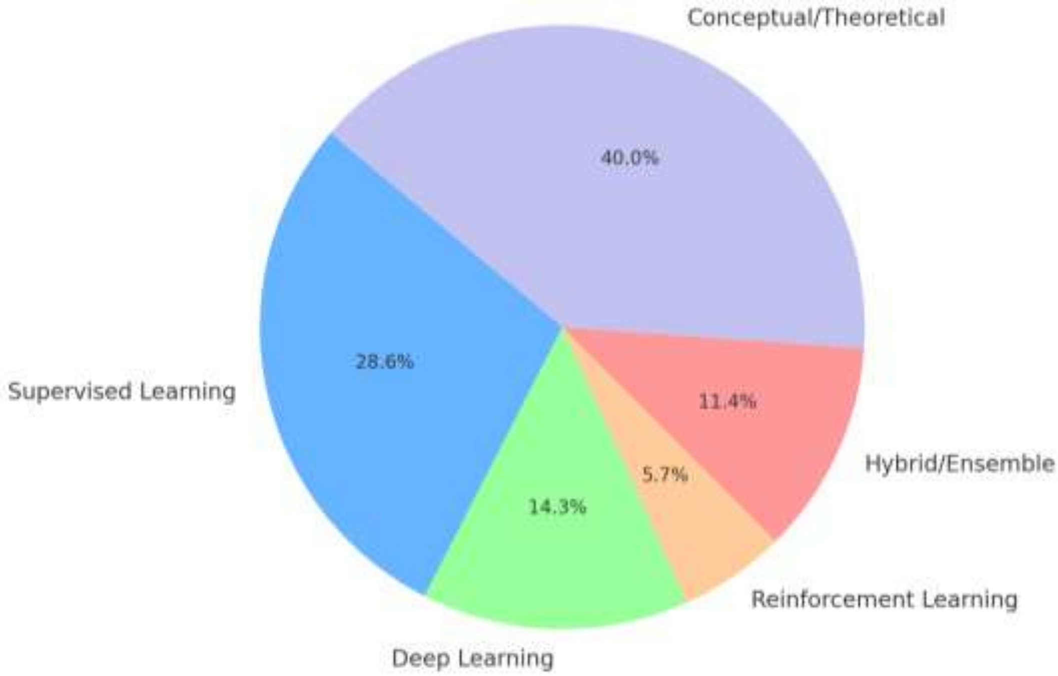

Figure 4: ML Algorithm Types across Studies

Figure 4 illustrates the distribution of machine learning (ML) study types, highlighting that Conceptual/Theoretical research dominates with 40%, reflecting a strong focus on frameworks and policy-level insights rather than algorithmic implementation. Supervised Learning follows at 28.6%, showing its widespread use in applied contexts such as classification and regression tasks. Deep Learning accounts for 14.3%, indicating its growing adoption, particularly in areas requiring high computational power like image or text processing. Hybrid/Ensemble methods make up 11.4%, suggesting moderate interest in model combination strategies to boost performance. Reinforcement learning, at just 5.7%, remains the least utilized, likely due to its complexity and domain-specific application requirements. This distribution points to a research trend still heavily grounded in theoretical development, with practical ML deployment gradually emerging.

4.1.2.2 ML Algorithm Types Across Studies

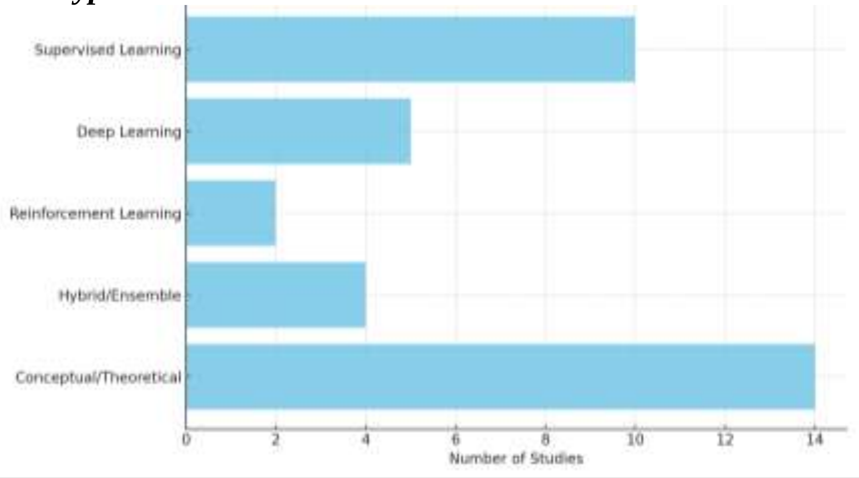

Figure 5: ML Algorithm Types across Studies

4.1.3 Evaluation Metrics

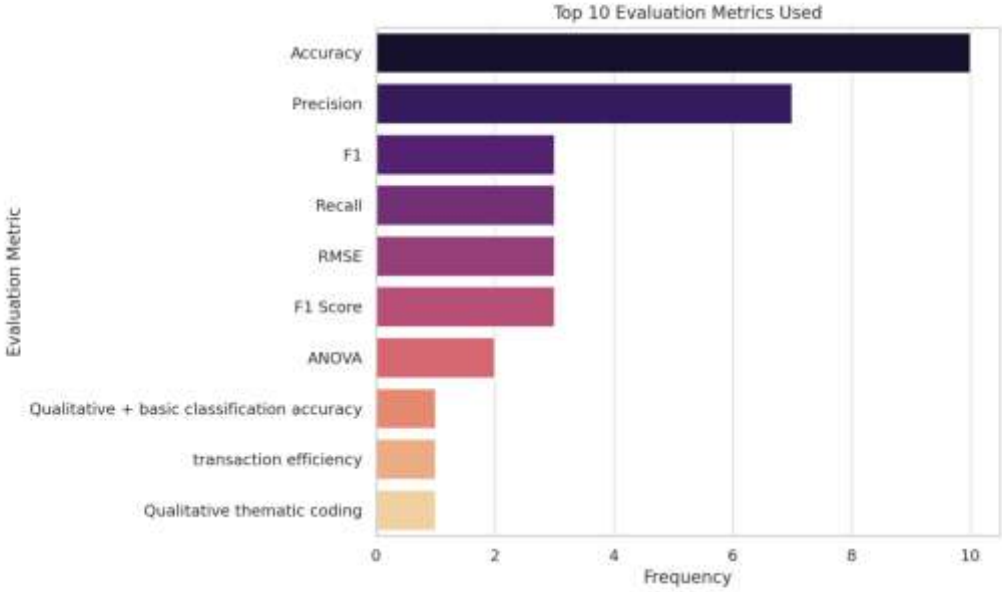

Figure 6: Top Ten Evaluation Metrics across Reviewed Papers

Figure 6 displays the top 10 evaluation metrics used in studies on machine learning applications for smart governance. Accuracy is the most frequently used metric, appearing in 10 studies, indicating a strong preference for straightforward performance measurement. Precision follows with 7 mentions, reflecting an emphasis on the correctness of positive predictions. Other commonly used metrics include F1, Recall, RMSE, and F1 Score, each cited 3 times, showing a balanced use of metrics that evaluate both classification and regression models. Less common metrics such as ANOVA, transaction efficiency, qualitative thematic coding, and a combination of qualitative and classification accuracy suggest a mix of both statistical and interpretive evaluation methods. Overall, the chart highlights a predominant reliance on standard classification metrics, especially accuracy and precision, while also recognizing more diverse approaches in a smaller number of studies.

4.1.4 Use of Specific Dataset

Figure 7 below illustrates the proportion of studies that used a specific dataset versus those that did not. A significant majority—**93.1%**—of the studies did not utilize a specific dataset, while only **6.9%** did. This indicates a heavy reliance on general or unspecified data sources in the reviewed literature, highlighting a key limitation in empirical robustness and reproducibility. The low use of specific datasets suggests a need for more data-driven, context-specific approaches in machine learning applications for governance research.

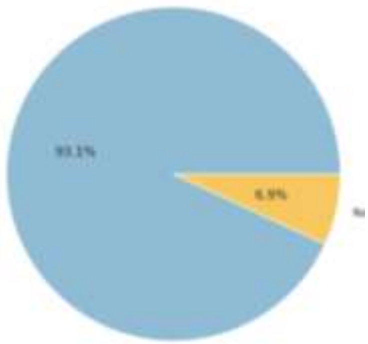

Figure 7: Use of Specific Dataset across Reviewed Papers

4.1.5 Research Focus

Table 5: Research Focus across Reviewed Papers

Research Focus	**Frequency**
Conceptual analysis of ML in public administration	1
ML modeling of organizational outcomes	1
ML for public sector HR planning	1
Public value theory and AI integration	1
Trust and ethics in algorithmic governance	1
Strategic frameworks for AI in public sector	1
ML for government transparency and fraud detection	1
Data mining in project governance	1
ML in anti-corruption and procurement systems	1
Big data governance in public administration	1
Smart governance policy for developing countries	1
Theoretical link between ML and organizational learning	1
ML for textual analysis in public sector communication	1
ML-enhanced knowledge management in engineering industries	1
ML adoption strategy in financial firms	1
Automated decision-making in strategy management	1
ML in Education 4.0 EIMS systems	1
ML with open data in smart city development	1
ML for HR performance and strategic analytics	1

Knowledge management models for smart campuses	1
Deep learning for organizational decision-making	1
ML in healthcare operations during COVID-19	1
Student performance prediction in Sub-Saharan higher education	1
ML for school performance prediction and educational governance	1
AI integration in academic governance systems	1
AI for smart governance and inclusive policy	1
Blockchain, ML and urban digital governance	1
ML applications in financial risk management	1
AI's organizational impact in news media	1

Table 5 reveals a highly diverse range of research focuses, with each topic addressed only once, indicating a fragmented but exploratory landscape. Key themes include the integration of machine learning (ML) into core public administration areas such as human resources, transparency, governance frameworks, education, and healthcare. The presence of niche areas—like blockchain integration, smart campuses, and textual analysis—suggests that scholars are probing various specific use cases without clear concentration on a dominant subfield. This dispersion points to an emerging but still maturing field, where foundational concepts and strategic models are being tested across different public sector domains.

4.1.5 Addressed Gaps

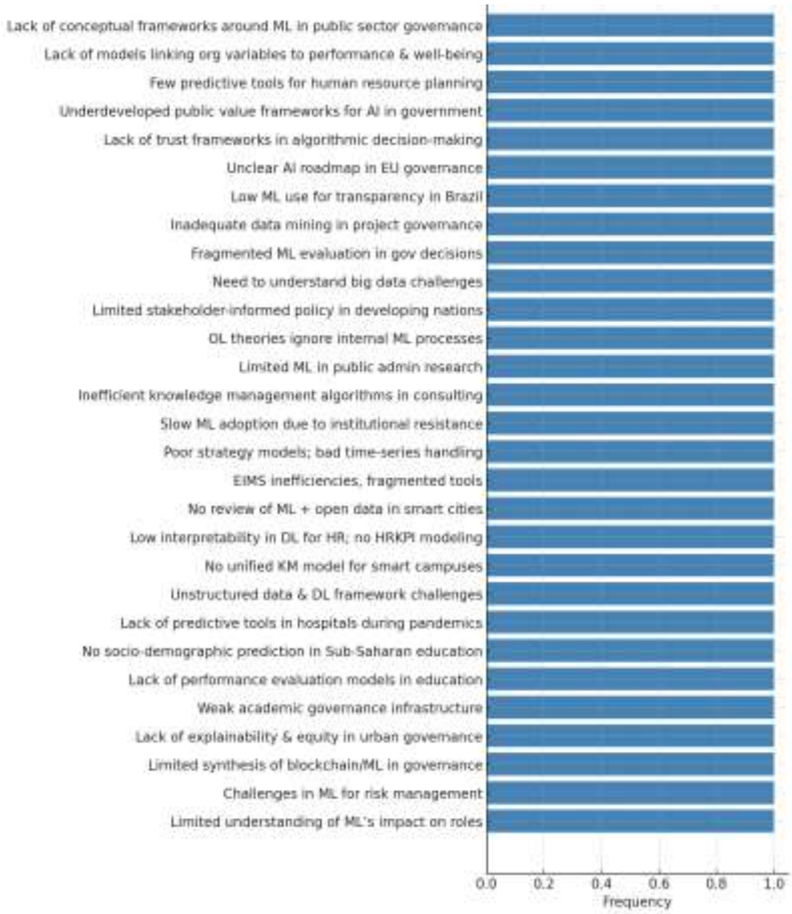

Figure 8: Addressed Gaps across Reviewed Papers

From Figure 8, the gaps identified across the reviewed literature are diverse and span conceptual, methodological, policy, and sector-specific domains. A significant number of gaps point to the lack of foundational frameworks and theoretical models guiding the use of ML in governance contexts, revealing a need for more holistic and interdisciplinary research. On the technical side, challenges like low interpretability, fragmented data systems, and limited predictive modeling capabilities signal the early-stage application of ML in real-world governance. From a policy perspective, the absence of roadmaps and stakeholder-driven strategies, particularly in developing regions, underscores uneven development. Sector-specific issues, such as healthcare during pandemics or education in Sub-Saharan Africa, highlight critical areas where ML remains underutilized, limiting its potential societal impact.

4.1.6 Unaddressed Gaps

Thematic Classification of Unaddressed Gaps

1. Lack of Empirical Validation & Real-World Testing

- No empirical testing or specific algorithm evaluation.

- No empirical testing or real-world application.

- No empirical validation; only theoretical propositions.

- Lacks empirical testing or case validation.

- No specific ML framework or empirical validation.

- Focus limited to one institution; no algorithm comparison.

- Small scale; lacks algorithm comparison.

- Small dataset; needs testing on real industry scale.

- No real-world datasets; limited scalability discussion.

- Long-term impact of tools not validated.

2. Limited Scalability & Generalizability

- Limited to EU context; no external validation.

- No generalizability test across different regions/countries.

- Lack of cross-domain application testing.

- Scalability and adaptation to other legal systems not discussed.

- No algorithmic details; unclear scalability.

3. Absence of Algorithmic Implementation

- No algorithmic implementation or KPIs.

- No original algorithmic implementation or testing.

- No implementation of proposed technologies.

- No ML implementation or predictive validation.

- No specific ML algorithm details or quantitative evaluation.

4. Weak Evaluation or Performance Issues

- Low recall; limited by training data size.

- High computational cost; interpretability not deeply addressed.

- Few real-time deployments; reinforcement learning underexplored.

- No novel algorithm or dataset introduced.

- No quantitative metrics or broader generalizability.

5. Ethical, Legal, and Fairness Gaps

- Ethical aspects and fairness not addressed.

- Need for integration with legal enforcement systems.

6. Conceptual/Qualitative Limitation

- No quantitative testing; based only on perceptions.

The unaddressed gaps in the reviewed literature can be broadly grouped into six key thematic shortcomings. Most prominently, there is a lack of empirical validation and real-world testing, with many studies remaining theoretical, limited in scale, or lacking robust algorithm comparison. Another major gap concerns limited scalability and generalizability, where findings are confined to specific regions or sectors without cross-domain or cross-country validation. Additionally, several papers demonstrate an absence of algorithmic implementation, offering no practical models, testing, or measurable KPIs. Evaluation weaknesses also emerge, such as poor performance metrics, high computational demands, and limited real-time applications. Ethical and legal issues form another significant category, where fairness, accountability, and regulatory integration are largely overlooked. Lastly, a conceptual/qualitative limitation is seen in works relying solely on perception-based insights without quantitative rigor. Together, these themes highlight the need for more comprehensive, tested, and ethically grounded ML applications in public governance.

4.2 Key Findings

Machine learning holds transformative potential for higher education governance, but current implementations are fragmented, under-theorized, and regionally inconsistent. There is a critical need for scalable, ethical, and context-aware ML frameworks that integrate strategic planning, transparency, and institutional goals. Below are the key findings from the reviewed papers.

1. Current State of ML in Higher Education Governance

ML adoption in higher education institutions (HEIs) is limited, fragmented, and primarily focused on predictive analytics for student performance rather than broader governance functions like policy formulation or strategic planning.

ML is being applied in areas such as:

i. Strategic planning and budgeting

ii. Performance monitoring

iii. Faculty evaluation

iv. Admissions forecasting

v. Curriculum design

2. Algorithm Trends and Performance

i. The most frequently used ML algorithms are:

ii. Support Vector Machines (SVM), Random Forest (RF), Logistic Regression, CNN, and LSTM.

iii. Accuracy and precision are the most commonly used evaluation metrics, showing a reliance on basic performance measures.

iv. Very few studies (only ~7%) used specific datasets, limiting reproducibility and contextual relevance.

3. Geographic and Contextual Disparities

i. Adoption of ML in governance is higher in developed countries, while low- and middle-income countries (LMICs) face infrastructural, policy, and capacity barriers.

ii. African studies point to ML's promise in addressing challenges like high student-faculty ratios and limited administrative capacity, but implementations are usually pilot-based and not scalable.

4. Conceptual and Methodological Gaps

i. There is no unified framework for applying ML in HEI governance.

ii. Existing studies lack attention to:

iii. Ethics, fairness, and algorithmic transparency

iv. Stakeholder participation and context-specific governance needs

v. Real-time deployment and explainable AI techniques

5. Smart Governance Potential and Technical Approaches

Emerging technologies like blockchain, MLOps, and decentralized governance models show promise in transforming governance through transparency, automation, and stakeholder inclusion.

However, most existing models are conceptual and lack real-world validation.

4.3. Discussion of Findings

This systematic literature review reveals a complex and evolving landscape in the application of machine learning (ML) within higher education governance. While the theoretical and technical potential of ML is widely recognized, practical implementation remains fragmented and underdeveloped. The findings suggest a misalignment between the promise of smart governance and its current operational reality in academic institutions.

1. Fragmented Implementation and Functional Limitations

Although higher education institutions (HEIs) generate rich datasets and possess the infrastructure for digital innovation, ML adoption has largely been restricted to narrow operational domains—primarily student performance prediction and risk analytics. Governance functions such as strategic planning, budget allocation, faculty assessment, and policy compliance remain relatively unexplored. This limited functional reach indicates that HEIs are not fully leveraging ML for strategic decision-making, reflecting both institutional inertia and a lack of integrative frameworks.

2. Algorithmic Popularity and Evaluation Practices

Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression emerged as the most frequently applied ML algorithms across reviewed studies. These models were typically evaluated using accuracy and precision metrics, suggesting a preference for easily interpretable and efficient solutions. However, the dominance of these metrics raises concerns regarding model generalizability, ethical fairness, and contextual performance—dimensions that are critical for governance-related decision-making but often overlooked in current implementations.

3. Regional Disparities and Contextual Barriers

The global distribution of ML research and deployment in HEIs exhibits pronounced disparities. While institutions in high-income countries are exploring more complex and strategic ML applications, those in low- and middle-income countries (LMICs) continue to grapple with infrastructural constraints, digital literacy gaps, and policy misalignment. Although ML has been piloted to address localized challenges—such as overcrowded classrooms and resource allocation—these efforts often lack scalability and institutional support. The absence of cross-regional standards or adaptation frameworks limits the broader impact of these innovations.

4. Conceptual and Methodological Gaps

A notable deficiency across the reviewed literature is the lack of coherent conceptual models guiding ML integration into academic governance. While technical blueprints—such as MLOps, blockchain-based decision systems, and decentralized architectures—are emerging, their application remains mostly conceptual. Furthermore, ethical considerations including algorithmic transparency, fairness, data protection, and stakeholder engagement are inconsistently addressed. This gap is especially problematic in governance settings, where decisions carry high stakes and affect diverse stakeholder groups.

5. Untapped Potential and Strategic Opportunities

Despite the fragmented nature of current practices, several studies point toward the transformative potential of ML in enhancing institutional agility, transparency, and performance optimization. Integrative models combining predictive analytics, real-time dashboards, and decentralized data management suggest a pathway toward scalable and adaptive smart governance frameworks. However, unlocking this potential requires empirical validation, policy alignment, and ethical safeguards that extend beyond technical feasibility.

4.3.1 Implications for Policy and Practice

The findings underscore the urgent need for standardized, inclusive, and ethically grounded frameworks for ML deployment in higher education governance. Institutions must move beyond isolated use-cases and invest in strategic digital infrastructures that support data-driven governance. At the same time, policymakers and developers must co-create governance solutions that prioritize transparency, fairness, and contextual adaptability. This will ensure that ML not only enhances administrative efficiency but also reinforces the core values of academic integrity, equity, and autonomy.

4.4 Recommendations for Further Study

Given the nascent and fragmented state of machine learning (ML) adoption in higher education governance, several key areas warrant further investigation. These recommendations aim to guide future research toward addressing critical gaps, improving scalability, and fostering ethical and context-sensitive implementations of ML technologies in academic institutions.

1. Development of Contextualized Governance Frameworks

Future studies should focus on designing and testing governance frameworks that are tailored to the unique structural, cultural, and policy environments of higher education institutions. This includes the development of modular, scalable models that can adapt to diverse regional contexts, especially in low- and middle-income countries (LMICs), where infrastructural limitations and digital inequality pose significant challenges.

2. Empirical Validation of ML Models in Real-World Settings

While many studies demonstrate promising results using simulated or secondary datasets, there is a critical need for real-world pilot studies that validate ML models within operational institutional environments. Research should explore the longitudinal performance, scalability, and integration of these models with existing administrative systems such as learning management systems (LMS), enterprise resource planning (ERP), and academic dashboards.

3. Exploration of Ethical and Governance Implications

Given the high-stakes nature of academic decision-making, further research is needed to address algorithmic fairness, transparency, explainability, and data governance. This includes the development of audit frameworks for ML algorithms used in governance, stakeholder-inclusive design processes, and policies that ensure accountability and ethical oversight.

4. Comparative Studies across Geopolitical Contexts

There is value in conducting cross-national comparative studies to examine how different institutional types and geopolitical settings affect the adoption and effectiveness of ML tools. Such studies could identify patterns of best practice, highlight transferability constraints, and inform the creation of adaptable ML governance toolkits.

5. Integration of Emerging Technologies

Interdisciplinary research exploring the integration of ML with blockchain, MLOps, and decentralized autonomous organizations (DAOs) should be expanded. These technologies offer new paradigms for transparency, participatory governance, and real-time decision-making in academia, yet remain underexplored in educational contexts.

6. Inclusion of Stakeholder Perspectives

Future research should place greater emphasis on stakeholder analysis, including the perceptions, needs, and concerns of students, faculty, and administrative personnel. Participatory action research and human-centered design methodologies can provide valuable insights into the acceptability, trust, and usability of ML systems in higher education governance.

To fully realize the potential of ML in transforming academic governance, future research must move beyond technical optimization to embrace holistic, inclusive, and empirically grounded approaches. Addressing these research priorities will be essential in shaping governance systems that are not only intelligent and efficient, but also equitable, ethical, and resilient.

4.5 Summary

This study conducted a comprehensive systematic literature review to evaluate the current landscape, capabilities, and limitations of machine learning (ML) applications in higher education governance. The findings reveal a growing but fragmented field, where ML has been primarily utilized for operational functions such as student performance prediction, with limited application to strategic governance tasks like institutional planning, faculty evaluation, or policy compliance.

The review identified Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression as the most frequently used algorithms, often evaluated through basic accuracy and precision metrics. However, most studies relied on general or simulated datasets, highlighting a significant gap in empirical robustness and real-world applicability. Furthermore, the implementation of ML in governance remains largely uneven across geographic regions, with low- and middle-income countries (LMICs) facing unique infrastructural and policy-related barriers.

The analysis also revealed a notable lack of conceptual frameworks, ethical guidelines, and stakeholder engagement in current ML governance models. While emerging technologies such as MLOps, blockchain, and decentralized governance offer promising pathways for innovation, their adoption in higher education contexts is still largely theoretical.

4.6 Conclusion

The integration of machine learning into higher education governance holds significant potential to enhance institutional efficiency, transparency, and adaptability. However, current efforts remain limited in scope, fragmented in execution, and underdeveloped in ethical and contextual considerations. To bridge this gap, future research must prioritize the development of adaptable governance frameworks, validate ML applications in real-world academic settings, and address ethical and stakeholder concerns comprehensively.

As higher education systems continue to evolve in response to digital transformation, there is a pressing need for cohesive, ethical, and scalable smart governance models. This study provides a foundational understanding of the current state of the field and lays the groundwork for future innovations that align technological advancements with institutional values and societal needs.

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