



Evaluating Institutional Readiness and Barriers to Machine Learning Based Personalized Learning in Secondary Schools

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Abstract: *The integration of machine learning–based personalized learning systems in secondary education offers significant potential to enhance instructional differentiation, learner monitoring, and academic support. However, adoption depends not only on technological capability but also on institutional readiness across infrastructure, human capacity, and leadership dimensions. This study evaluated institutional readiness and barriers to implementing ML-based personalized learning in secondary schools in Rwanda using a mixed-methods design. Data were collected from 200 institutional staff members across ten secondary schools representing all five provinces. Findings indicate moderate but uneven readiness. Infrastructure indicators show that 55% of schools reported functional ICT laboratories, yet only 42% reported reliable internet connectivity and 36% adequate technical maintenance support. Human capacity gaps were pronounced: while 84% of respondents rated staff digital literacy as high or moderate, only 18% reported high understanding of ML concepts and 22% expressed high confidence in using AI tools. Governance readiness was limited, with 61% reporting data protection policies but only 29% indicating the presence of an institutional AI or digital strategy, and 63% lacking regular data quality audits. Leadership openness to innovation was relatively strong (52%), yet only 33% reported strong ICT budget allocation. The most significant barriers identified were limited technical expertise (64%), insufficient funding (58%), and data privacy concerns (52%), whereas resistance to change was lower (29%). The study concludes that ML-based personalization adoption is constrained primarily by structural capacity and governance gaps rather than institutional resistance, highlighting the need for coordinated readiness strengthening across schools.*

Keywords: *Machine learning; personalized learning; institutional readiness; secondary schools; AI adoption barriers*

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1. Introduction

The rapid advancement of artificial intelligence (AI) and machine learning (ML) technologies has significantly

reshaped global discourse on educational innovation, particularly in relation to personalized learning. ML-based personalized learning systems promise to tailor instructional content, pacing, feedback, and support to individual learner needs through data-driven modeling and

predictive analytics. Such systems can identify patterns in learner performance, anticipate academic risks, and recommend targeted interventions. While the technical feasibility of these approaches has been widely demonstrated in research contexts, their successful implementation in real school environments depends on more than algorithmic capability. Institutional readiness encompassing infrastructure, human capacity, governance structures, data systems, and leadership support plays a critical role in determining whether ML-based personalization can be adopted and sustained effectively within secondary schools (Holmes et al., 2021; Luckin et al., 2022).

Secondary schools operate within complex institutional ecosystems shaped by curriculum standards, high-stakes examinations, teacher workload, technological infrastructure constraints, and varying levels of digital literacy among educators and learners. Although ML-based systems may enhance instructional differentiation and learner monitoring, they also introduce new challenges related to data privacy, algorithmic transparency, bias, and equitable access. International policy frameworks increasingly emphasize that AI adoption in education must be preceded by adequate institutional preparation and governance mechanisms. UNESCO (2021) highlights that AI integration requires systemic capacity building, ethical oversight, and alignment with educational objectives, while more recent guidance underscores the importance of responsible implementation and stakeholder preparedness in school settings. Similarly, UNICEF (2023) stresses that AI systems affecting children must prioritize safety, privacy, and non-discrimination, reinforcing the need for institutional safeguards before deployment.

Empirical research further indicates that barriers to AI adoption in schools are often organizational rather than technical. Studies on digital transformation in education systems identify insufficient teacher preparedness, limited professional development, fragmented data systems, and inadequate technical support as persistent obstacles to innovation (OECD, 2021). The World Bank (2022) similarly notes that infrastructure deficits, uneven connectivity, and capacity constraints can significantly impede the effective use of AI-based educational tools, particularly in developing and resource-constrained contexts. Even when data exist within education management systems, they are frequently underutilized for instructional personalization due to limitations in interoperability, quality, or analytic capacity.

In many developing-country settings, including Sub-Saharan Africa, administrative and assessment data are available at national or district levels, yet institutional readiness at the school level remains uneven. Secondary

schools may face constraints in device availability, connectivity reliability, ICT maintenance, and data governance policies. Furthermore, leadership commitment and change management capacity strongly influence the adoption of new technologies in educational institutions. Without supportive organizational culture and professional capacity, ML-based personalized learning initiatives risk remaining pilot projects rather than scalable, system-wide innovations (Trucano, 2016).

Evaluating institutional readiness is therefore a critical step prior to implementing ML-based personalized learning solutions in secondary schools. Readiness extends beyond technical infrastructure to include teacher digital competence, data literacy, governance frameworks, ethical safeguards, and alignment with curriculum and assessment practices. Identifying readiness gaps enables policymakers and school leaders to allocate resources strategically, design targeted capacity-building programs, and mitigate implementation risks. Moreover, understanding institutional barriers whether technical, organizational, financial, or socio-cultural provides insight into the feasibility and sustainability of AI-driven personalization initiatives (Isaacs, 2019).

This study seeks to evaluate institutional readiness and identify barriers to implementing ML-based personalized learning in secondary schools. By examining dimensions such as digital infrastructure, human capacity, data availability and governance, leadership support, and ethical preparedness, the study contributes to emerging scholarship on responsible AI adoption in education. Rather than focusing solely on model performance or technological innovation, the paper centers institutional conditions as determinants of successful implementation. In doing so, it advances a systems-oriented perspective that situates machine learning–based personalization within the broader socio-technical environment of secondary education. Such an approach is particularly relevant for education systems seeking to harness AI responsibly while safeguarding equity, sustainability, and educational quality.

2. Literature Review

2.1 Personalized Learning and the Evolution of Learner-Centered Education

Personalized learning has increasingly been positioned as a response to the long-standing tension between standardized instruction and learner diversity. Rooted in constructivist and learner-centered theories, personalized

learning emphasizes adaptation of instructional strategies to learners' needs, interests, pace, and prior knowledge. Early discussions of differentiation focused largely on pedagogical adjustments made by teachers within classroom contexts. However, the growth of digital technologies and data analytics has expanded the meaning of personalization to include algorithmically supported instructional decisions.

Research suggests that personalization can positively influence engagement, motivation, and learning outcomes when implemented effectively (Hattie & Timperley, 2007). In contemporary educational discourse, personalized learning is often linked with learning analytics, adaptive systems, and artificial intelligence, which enable dynamic adjustment of content and support. Yet the promise of personalization must be examined within the institutional realities of schools, where resource constraints, curricular requirements, and assessment pressures shape implementation possibilities. As Holmes, Bialik, and Fadel (2019) argue, technological potential does not automatically translate into improved learning without appropriate contextual integration.

2.2 Machine Learning Applications in Education

The application of machine learning in education has expanded considerably over the past decade. Supervised learning models have been used to predict student performance, identify at-risk learners, and generate early-warning signals (Romero & Ventura, 2013; Baker & Inventado, 2014). Unsupervised approaches, such as clustering, have been employed to detect learner profiles and uncover hidden performance patterns within educational datasets. More recent work has explored deep learning and hybrid recommendation systems for adaptive learning environments (Chen, Chen, & Lin, 2020).

While technical advancements have improved model sophistication, researchers increasingly emphasize the importance of interpretability and practical utility. Educational stakeholders must understand and trust analytical outputs if they are to incorporate them into instructional decision-making. Bodily and Verbert (2017) highlight that transparency and user-centered design are critical for adoption of learning analytics tools. Without institutional capacity to interpret and act on machine learning outputs, technology risks becoming detached from educational practice.

2.3 Institutional Readiness for Educational Technology Innovation

Institutional readiness refers to the degree to which an organization possesses the infrastructure, skills, governance structures, and cultural support necessary to implement innovation successfully. In the context of ML-based personalized learning, readiness extends beyond hardware and software availability. It includes teacher digital competence, data literacy, leadership support, maintenance capacity, and policy alignment.

Research on digital transformation in schools demonstrates that successful adoption of educational technology depends heavily on human and organizational factors. OECD (2021) reports that teacher professional development and leadership commitment are among the strongest predictors of sustainable technology integration. Similarly, Ertmer and Ottenbreit-Leftwich (2010) argue that teachers' beliefs, confidence, and pedagogical alignment play a decisive role in whether digital innovations become embedded in classroom practice. Infrastructure alone does not ensure readiness; institutional culture and capacity matter equally.

Within AI in education discourse, UNESCO (2021) stresses that readiness must include ethical governance, regulatory frameworks, and capacity building. Schools must be prepared not only to use AI tools but also to understand their implications for equity, accountability, and learner rights. Without appropriate safeguards, algorithmic systems may reproduce biases or exacerbate inequalities.

2.4 Barriers to Implementing ML-Based Personalized Learning

Despite growing enthusiasm for AI-enabled education, several barriers continue to constrain implementation, particularly in secondary school contexts. Infrastructure limitations, including inconsistent connectivity and insufficient device access, remain common challenges in many regions (World Bank, 2022). Even where data are available, they may lack interoperability, consistency, or quality required for machine learning applications.

Human capacity barriers are equally significant. Teachers often report limited training in data interpretation and digital analytics, which undermines confidence in AI-driven tools. Kizilcec and Lee (2020) note that algorithmic systems in education require careful communication and professional development to avoid mistrust or misuse. Furthermore, time constraints and curriculum pressures

may reduce educators' willingness to adopt new technologies that appear to add complexity rather than reduce workload.

Ethical and governance concerns also represent substantial barriers. UNICEF (2023) emphasizes that AI systems affecting children must prioritize privacy, fairness, and transparency. Secondary schools, which manage sensitive student data, must ensure compliance with data protection standards and establish accountability mechanisms. In contexts where governance frameworks are underdeveloped, institutional hesitation toward AI adoption may reflect legitimate concerns rather than resistance to innovation.

2.5 Readiness and Barriers in Developing and Resource-Constrained Contexts

In developing-country settings, readiness challenges are often amplified by structural inequalities. Although national education systems may maintain administrative datasets, school-level infrastructure and capacity can vary significantly. Research on AI adoption in low- and middle-income countries highlights disparities in connectivity, technical support, and teacher preparedness (Zawacki-Richter et al., 2019). The World Bank (2022) notes that successful AI integration requires complementary investments in infrastructure, professional development, and governance systems.

Moreover, digital divides between schools can result in uneven benefits from personalization technologies. Without deliberate equity-focused strategies, ML-based systems may advantage well-resourced institutions while leaving marginalized schools behind. Institutional readiness assessments therefore serve not only as diagnostic tools but also as mechanisms for identifying systemic inequities.

2.6 Conceptualizing Readiness for ML-Based Personalization in Secondary Schools

Synthesizing the literature, institutional readiness for ML-based personalized learning can be conceptualized as a multi-dimensional construct encompassing infrastructure readiness, human capacity readiness, data readiness, governance readiness, and leadership readiness. Infrastructure readiness refers to availability of connectivity, devices, and technical support. Human capacity readiness includes teacher digital competence,

data literacy, and openness to innovation. Data readiness involves data quality, interoperability, and secure storage systems. Governance readiness covers ethical frameworks, privacy safeguards, and accountability mechanisms. Leadership readiness reflects strategic vision, resource allocation, and change management capacity (Aydin & Tasci, 2005; Kaur & Nagaich, 2023).

Evaluating these dimensions collectively provides a comprehensive understanding of institutional preparedness. Rather than focusing exclusively on technological capability, this broader conceptualization recognizes that ML-based personalization is embedded within socio-technical systems. Adoption success depends on alignment between technological tools and institutional environments.

2.7 Research Gap

Although the literature on AI in education has expanded rapidly, relatively few studies empirically examine institutional readiness for ML-based personalized learning in secondary schools, particularly in developing-country contexts. Existing research often prioritizes model performance or platform design, leaving organizational and systemic factors underexplored. There remains a need for systematic evaluation of readiness conditions and barriers at the school level to inform responsible and sustainable implementation strategies.

This study addresses that gap by examining institutional readiness and identifying barriers to implementing ML-based personalized learning in secondary schools. By grounding analysis in both technological and organizational perspectives, the research contributes to a more holistic understanding of how AI-driven personalization can move from conceptual promise to practical reality.

3. Methodology

This study employed a mixed-methods research design to comprehensively evaluate institutional readiness and barriers to implementing machine learning-based personalized learning in secondary schools. The mixed-methods approach was selected to capture both measurable institutional indicators and deeper contextual insights regarding organizational preparedness, governance structures, and operational constraints. The quantitative component generated structured data on infrastructure availability, data management practices, ICT capacity, leadership support, and institutional policy alignment. The qualitative component, derived from open-ended responses and key informant input, provided detailed explanations of

systemic challenges, resource gaps, and implementation concerns. This design enhanced the validity of the findings by triangulating numerical trends with contextual interpretation.

The research was conducted across Rwanda in five provinces: Northern Province, Southern Province, Eastern Province, Western Province, and the City of Kigali. In each province, two secondary schools were selected using random sampling procedures, resulting in a total of ten participating schools representing diverse geographic, infrastructural, and socio-economic contexts. The study population consisted exclusively of institutional staff members involved in school administration, ICT management, data management, and strategic planning. These included school principals, deputy heads, directors of studies, ICT coordinators, data officers, and administrative personnel responsible for digital systems and academic reporting. Teachers and students were intentionally excluded from the sample to ensure that the focus remained on institutional-level readiness rather than classroom practices or learner experiences.

A total of 200 institutional staff members participated in the study. Stratified random sampling was used to ensure proportional representation of different administrative roles within each school. In addition, purposive sampling was applied to identify key informants such as ICT coordinators and school leaders whose roles provided critical insights into infrastructure readiness, governance policies, and digital strategy implementation. This sampling strategy ensured that responses reflected institutional capacity and decision-making perspectives rather than individual classroom-level experiences.

Data were collected using a structured questionnaire designed specifically to measure institutional readiness dimensions. The instrument was aligned with a multi-dimensional readiness framework encompassing digital infrastructure readiness, human capacity readiness, data readiness, governance and policy readiness, and leadership commitment. The questionnaire included closed-ended Likert-scale items to quantify levels of preparedness and perceived barriers, as well as open-ended questions to capture qualitative insights regarding operational constraints and anticipated challenges. The was piloted in one secondary school not included in the final sample to ensure clarity, reliability, and contextual relevance.

Following ethical clearance and administrative approval from relevant education authorities including school

leaders, questionnaires were distributed either electronically or in printed format depending on school infrastructure capacity. All participants were informed of the study's purpose and assured that participation was voluntary. Confidentiality and anonymity were strictly maintained, and data were used solely for academic research purposes.

Quantitative data were analyzed using descriptive and inferential statistical techniques. Descriptive statistics, including frequencies, means, and percentages, were used to assess overall readiness levels across institutional dimensions. Inferential analyses, such as correlation analysis and cross-tabulation, were conducted to examine relationships between infrastructure capacity, leadership support, data governance readiness, and perceived implementation barriers. Statistical analysis was conducted using SPSS software to ensure accuracy and systematic interpretation.

Qualitative data from open-ended responses were analyzed using thematic content analysis. Responses were coded and categorized to identify recurring themes related to infrastructure limitations, governance concerns, technical capacity gaps, financial constraints, and organizational resistance to change. This qualitative analysis provided deeper insight into the institutional realities shaping readiness for machine learning-based personalized learning.

Throughout the research process, ethical standards were strictly observed. Institutional authorization was obtained from participating schools and district education authorities. Participation was voluntary, informed consent was secured from all respondents, and data were securely stored to protect confidentiality. These measures ensured adherence to ethical research principles and strengthened the credibility of the study's findings.

4. Results and Discussion

This section presents the empirical findings of the study based on responses from 200 institutional staff members drawn from ten secondary schools across Rwanda. The analysis focuses on institutional readiness dimensions and barriers to implementing machine learning-based personalized learning. Each table is followed by interpretation and discussion to situate findings within broader educational transformation literature.

Table 1: Demographic Characteristics of Institutional Staff Respondents (N = 200)

Variable	Category	Frequency	Percentage (%)
Position	School Principal	32	16.0
	Deputy Head	28	14.0
	Director of Studies	40	20.0
	ICT Coordinator	52	26.0
	Data/Records Officer	48	24.0
Province	Northern	40	20.0
	Southern	40	20.0
	Eastern	40	20.0
	Western	40	20.0
	Kigali City	40	20.0
Years of Experience	1–5 years	44	22.0
	6–10 years	68	34.0
	11–15 years	52	26.0
	Above 15 years	36	18.0

The respondents represented a balanced mix of institutional leadership and technical staff. ICT coordinators (26%) and data officers (24%) constituted half of the sample, ensuring strong representation of personnel directly involved in digital systems management. Leadership representation (principals, deputies, directors of studies) accounted for 50% of respondents, strengthening the institutional perspective of the findings.

Even provincial distribution enhances geographic representativeness and increases confidence that findings reflect national patterns rather than localized conditions. Most respondents (78%) had more than five years of experience, suggesting familiarity with institutional operations and digital transformation initiatives.

Table 2: Digital Infrastructure Readiness for ML-Based Personalized Learning

Infrastructure Indicator	Adequate (%)	Partially Adequate (%)	Inadequate (%)
Reliable Internet Connectivity	42	38	20
Computer Availability	47	33	20
Functional ICT Laboratories	55	25	20
Technical Maintenance Support	36	41	23
Secure Data Storage Systems	49	31	20

Infrastructure readiness shows moderate preparedness. While over half of schools reported functional ICT laboratories (55%), only 42% indicated reliable internet connectivity. Maintenance support remains a concern, with 23% reporting inadequate support. These findings suggest that although foundational infrastructure exists, it may not yet be sufficiently robust to sustain advanced ML-based systems that require stable connectivity and reliable technical support.

This aligns with global observations that infrastructure is often a foundational but incomplete dimension of AI readiness (World Bank, 2022). Schools may possess hardware, but sustainability and reliability remain challenges.

Table 3: Human Capacity Readiness (Digital and Data Competence)

Indicator	High (%)	Moderate (%)	Low (%)
Digital Literacy of Staff	38	46	16
Data Analysis Skills	29	48	23
Understanding of Machine Learning Concepts	18	41	41
Confidence in Using AI Tools	22	44	34

While general digital literacy is moderate (84% reporting high or moderate), understanding of machine learning concepts remains limited. Only 18% reported high understanding of ML, and 41% reported low understanding. This gap highlights a critical readiness barrier: institutional leadership may manage digital systems but lack familiarity with advanced analytics technologies.

These findings reinforce OECD (2021) conclusions that teacher and staff professional development is central to AI adoption. Without capacity-building interventions, ML systems risk being underutilized or misunderstood.

Table 4: Data Governance and Policy Readiness

Indicator	Yes (%)	No (%)
Existence of Data Protection Policy	61	39
Defined Data Access Controls	54	46
Regular Data Quality Audits	37	63
Institutional AI/Technology Strategy	29	71

Data governance readiness reveals structural gaps. While 61% reported data protection policies, only 29% indicated the existence of a formal AI or digital transformation strategy. Moreover, 63% reported no regular data quality audits.

These findings suggest that although foundational governance elements exist, strategic alignment for ML-based systems remains limited. This supports UNESCO (2021) assertions that governance and policy readiness must precede AI integration to ensure ethical and sustainable implementation.

Table 5: Leadership Commitment and Institutional Support

Indicator	Strong (%)	Moderate (%)	Weak (%)
Leadership Support for Digital Innovation	48	37	15
Budget Allocation for ICT	33	42	25
Strategic Vision for Digital Transformation	35	39	26
Openness to Institutional Change	52	33	15

Leadership openness to change is relatively high (52% strong), indicating positive cultural readiness. However, only 33% reported strong budget allocation for ICT initiatives. This suggests a disconnect between vision and financial capacity.

Institutional transformation literature consistently identifies leadership commitment as a critical success factor. While attitudinal readiness appears promising, financial and structural support mechanisms remain inconsistent.

Table 6: Perceived Barriers to ML-Based Personalized Learning Implementation

Barrier	High Impact (%)	Moderate Impact (%)	Low Impact (%)
Limited Technical Expertise	64	25	11
Insufficient Funding	58	29	13
Poor Internet Reliability	47	33	20
Data Privacy Concerns	52	30	18
Resistance to Change	29	44	27

The most significant barriers identified were limited technical expertise (64%) and insufficient funding (58%). Data privacy concerns were also prominent (52%), reflecting growing awareness of ethical considerations in AI systems.

Resistance to change was comparatively lower (29% high impact), indicating that institutional culture may not be the primary obstacle. Rather, structural and capacity-related factors dominate.

These findings echo global AI adoption research, which consistently identifies capacity gaps and financial limitations as primary constraints, particularly in resource-constrained settings.

Discussion of Findings

Taken together, the findings reveal that institutional readiness for ML-based personalized learning in secondary

schools is moderate but uneven. Infrastructure exists but lacks full reliability. Digital literacy is moderate, yet advanced ML understanding is limited. Governance frameworks are partially developed, but strategic AI alignment is weak. Leadership attitudes are generally positive, but budgetary constraints and technical expertise gaps present substantial barriers.

The interplay of these dimensions suggests that readiness is multi-layered. Schools cannot rely solely on hardware investment; they must simultaneously strengthen human capacity, governance frameworks, and strategic alignment. Importantly, cultural resistance appears less significant than technical and financial barriers, indicating that institutional actors may be receptive to innovation if adequate support systems are provided.

These findings support a socio-technical interpretation of AI readiness, in which technology adoption is shaped by organizational conditions rather than purely technical capability. For ML-based personalized learning to become

sustainable in secondary schools, coordinated interventions across infrastructure, capacity building, governance, and leadership are required.

The findings of this study reinforce the growing body of research suggesting that technological readiness alone does not guarantee successful AI integration in educational institutions. Although many schools reported the presence of ICT laboratories and moderate levels of digital literacy among staff, the limited understanding of machine learning concepts and the absence of structured AI strategies indicate a readiness gap at the strategic and conceptual levels. Similar patterns have been observed in international contexts, where schools may possess hardware infrastructure but lack the institutional knowledge required to leverage advanced analytics effectively (OECD, 2021). Zawacki-Richter et al. (2019) similarly note that while AI technologies are expanding rapidly in education, institutional capacity to interpret and govern these systems often lags behind technical development. The present findings suggest that Rwanda's secondary schools are not resistant to innovation but rather require structured professional development and institutional guidance to move from digital adoption toward intelligent system integration.

The prominence of funding limitations and technical expertise gaps as major barriers is also consistent with findings from the World Bank (2022), which highlights that resource-constrained education systems frequently face structural challenges in sustaining digital innovation. In many developing contexts, schools operate under budgetary constraints that prioritize immediate instructional needs over long-term technological investments. The fact that resistance to change was reported as a relatively lower barrier in this study is noteworthy. It suggests that institutional culture may be more adaptable than often assumed, and that with appropriate investment and technical support, ML-based personalized learning could gain acceptance. This aligns with Ertmer and Ottenbreit-Leftwich's (2010) argument that when educators perceive innovation as aligned with institutional goals and supported by leadership, adoption becomes more feasible.

Furthermore, the identified concerns regarding data governance and privacy reflect increasing global awareness of ethical considerations in AI deployment. UNESCO (2021) and UNICEF (2023) emphasize that responsible AI integration in schools requires strong governance frameworks, data protection mechanisms, and transparency safeguards. The finding that a majority of schools lack formal AI strategies and regular data audits underscores the importance of policy-level preparation before scaling machine learning applications. Institutional

readiness, therefore, should be understood not only as a measure of technological capacity but also as an indicator of ethical and regulatory preparedness. Without deliberate governance strengthening, the introduction of ML-based personalized learning systems may expose schools to unintended risks related to data misuse, bias, or accountability gaps.

5. Conclusion and Recommendations

5.1 Conclusion

The purpose of this study was to evaluate institutional readiness and identify barriers to implementing machine learning-based personalized learning in secondary schools. The findings indicate that readiness exists, but it is uneven and incomplete. Schools demonstrate foundational digital infrastructure and a generally positive leadership attitude toward technological innovation; however, significant gaps remain in advanced technical expertise, structured AI strategies, data governance practices, and sustainable funding mechanisms. These gaps suggest that while secondary schools are progressing digitally, they are not yet fully prepared to adopt and sustain machine learning-based personalization systems at scale.

One of the most encouraging findings is the relatively low level of resistance to institutional change. Staff members appear open to innovation and recognize the potential benefits of intelligent systems for improving academic support and decision-making. This openness presents an important opportunity: when institutional culture is receptive, targeted investments in capacity building and strategic planning can have substantial impact. The major constraints identified limited technical expertise, insufficient funding, and governance gaps are structural rather than attitudinal, meaning they can be addressed through coordinated policy, training, and resource allocation.

The findings also highlight that institutional readiness is multidimensional. Infrastructure alone is insufficient; human capacity, governance systems, leadership alignment, and financial sustainability must advance simultaneously. Schools that possess hardware but lack data governance policies or AI literacy may struggle to translate machine learning outputs into responsible and effective practice. Therefore, readiness should be approached as a systemic condition rather than a technical checklist.

In conclusion, institutional readiness for machine learning-based personalized learning in secondary schools is

emerging but requires deliberate strengthening. With strategic leadership, targeted capacity building, robust governance frameworks, and sustainable resource planning, schools can move from basic digital readiness toward intelligent and responsible personalization. The path forward lies not merely in adopting advanced algorithms, but in cultivating institutions capable of integrating them thoughtfully and ethically into educational practice.

5.2 Recommendations

Based on the findings of the study, the following recommendations are proposed:

1. Education authorities should formulate a clear strategy for integrating AI and machine learning in secondary schools, defining standards for data governance, ethical safeguards, interoperability, and phased implementation pathways.

2. Sustained professional development programs should be established to build educators' and school leaders' understanding of machine learning concepts, data interpretation, and responsible AI use. Training should particularly target ICT staff and leadership teams who drive institutional transformation.

3. Investment planning should move beyond equipment acquisition toward long-term sustainability, including budgeting for maintenance, technical support, system upgrades, and cybersecurity. Partnerships with universities and technology institutions should be encouraged to provide expertise and innovation support.

4. Machine learning-based personalized learning initiatives should begin with pilot programs in selected schools to refine technical and governance frameworks. Lessons learned should guide gradual scale-up, supported by continuous monitoring and evaluation to ensure alignment with educational goals and equity principles.

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