



Artificial intelligence in Zambian education: A systematic literature review and conceptual framework for sustainable resource allocation

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ABSTRACT

Zambian educational institutions face persistent challenges in allocating material, financial, and human resources fairly and efficiently. These challenges include uneven access to infrastructure and learning materials, staffing constraints, weak information systems, and limited capacity for data-informed planning. Recent scholarship suggests that artificial intelligence (AI) can support forecasting, decision support, monitoring, and optimisation, while also highlighting risks associated with data quality, infrastructure, algorithmic bias, privacy, and unequal institutional capacity. This article presents a systematic literature review (SLR) examining the relevance of AI to sustainable educational resource allocation, with particular attention to the Zambian context. Searches were conducted across Scopus, Web of Science, the Education Resources Information Center (ERIC), and Google Scholar for peer-reviewed journal articles published between 2021 and 2026 and were structured and reported with reference to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. The final coded corpus comprised 180 studies. The synthesis identifies three principal application areas, predictive analytics, teacher allocation, and infrastructure monitoring, alongside supporting domains such as financial planning and policy simulation. Drawing on the Resource-Based View, Dynamic Capabilities Theory, and AI and machine-learning perspectives, the review develops a conceptual framework that integrates AI-enabled allocation with governance, human oversight, contextual adaptation, and accountability. The review indicates substantial potential for AI-supported resource management, but the evidence does not justify assuming automatic gains in efficiency or equity. For Zambia, implementation is likely to depend on reliable data, connectivity, institutional capability, professional development, appropriate governance, and locally adapted models. The proposed framework therefore provides a basis for subsequent empirical validation rather than a claim of demonstrated implementation effectiveness.

Keywords: Artificial Intelligence, Conceptual Framework, Educational Administration, Predictive Analytics, Systematic Literature Review, Sustainable Resource Allocation

I. INTRODUCTION

Artificial intelligence (AI) is increasingly relevant to educational systems, not only through teaching and learning applications but also through data-informed administration, decision support, and system management. Recent systematic reviews describe a rapidly expanding and diverse artificial intelligence in education (AIED) literature that includes predictive and analytical applications, administrative support, personalised learning, and governance questions (Wang et al., 2024; Mustafa et al., 2024). At the same time, this literature cautions against treating AI as inherently beneficial, with data quality, human oversight, privacy, fairness, and unequal technological capacity remaining central concerns (Ifenthaler et al., 2024; Zhu et al., 2025). Within educational administration, these concerns are especially relevant to the allocation of scarce material, human, and financial resources. AI can provide analytical support for forecasting demand, identifying patterns, comparing allocation options, monitoring assets, and informing administrative decisions. Yet the usefulness of these capabilities depends on the quality of the underlying information, the capacity of users to interpret outputs, and the institutional authority and governance arrangements

through which recommendations are acted upon (Ifenthaler et al., 2024; Wang et al., 2024). AI is therefore better examined as part of an organisational system than as a stand-alone technical solution.

International policy frameworks reinforce this systems perspective. The United Nations Educational, Scientific and Cultural Organization (UNESCO) places privacy, equity, transparency, safety, and capacity development at the centre of human-centred AI adoption in education (UNESCO, 2023). The Organisation for Economic Co-operation and Development (OECD) similarly emphasises infrastructure, governance, interoperability, and human competence as interdependent conditions for effective and equitable digital transformation (OECD, 2023). More recent OECD evidence indicates that generative AI can support education when guided by appropriate pedagogical and institutional principles, but technological capability alone does not guarantee meaningful or equitable outcomes (OECD, 2026). These conditions are particularly important in African and other low-resource educational settings, where infrastructure, professional capability, institutional readiness, and contextual fit vary substantially. Evidence from Namibia shows that teachers' confidence, perceived relevance, attitudes, and professional preparation shape engagement with AI, while research involving educators in Lesotho, Rwanda, and Nigeria similarly points to uneven conditions for introducing advanced educational technologies (Jatileni et al., 2024; Theodorio et al., 2024). Models developed in high-income settings therefore cannot be assumed to transfer directly to Zambia without attention to local data structures, staffing patterns, infrastructure, policy requirements, and professional practices.

Within Zambia, the evidence base is beginning to document engagement with AI, particularly in higher education, but remains limited in relation to school-level administration and resource allocation. A 2026 multi-institutional study of 1,829 university students found widespread awareness and use of ChatGPT in Zambia, alongside concerns about risk, responsible use, and institutional guidance (Mudenda et al., 2026). This provides evidence of an emerging national AI environment, but it should not be conflated with evidence that AI is already being used systematically to allocate teachers, materials, infrastructure, or school finances. The Zambian policy environment is also moving toward greater digitalisation. Recent policy direction places increasing emphasis on digital infrastructure, data systems, capacity building, and AI as part of wider digital transformation (Ministry of Education, 2025; Ministry of Technology and Science, 2024). These developments create a policy basis for research on AI-supported educational management, while also making evidence concerning feasibility, governance, and equity increasingly important. Policy readiness is therefore treated in this review as an enabling condition rather than as evidence of implementation success.

Taken together, the literature reveals three connected but insufficiently integrated strands of evidence. International AIED research provides substantial evidence concerning predictive and analytical applications, decision support, and governance challenges; African research demonstrates that infrastructure, professional capability, institutional readiness, and contextual fit shape the feasibility of AI adoption; and emerging Zambian evidence shows increasing engagement with AI without establishing a mature evidence base for AI-enabled educational resource allocation. What remains insufficiently developed is an integrated account of how these strands can inform sustainable allocation of material, human, and financial resources in Zambian schools. The research gap is therefore not simply the absence of studies on AI in Zambia. It concerns the limited synthesis connecting AI capabilities, resource-management requirements, institutional conditions, and governance safeguards within a framework designed for the Zambian educational context. This review extends earlier work examining ethical pathways for artificial intelligence adoption in resource-constrained educational contexts (Ndumba, 2026). In particular, there is limited integration of predictive analytics, teacher allocation, infrastructure monitoring, financial planning, decision support, human oversight, and contextual adaptation as interdependent components of sustainable resource management. Technological solutions developed in substantially different institutional environments cannot be assumed to transfer directly to Zambian schools.

The present systematic literature review (SLR) addresses this gap by synthesising recent peer-reviewed evidence on AI applications relevant to educational resource allocation and examining its implications for Zambia. The review focuses on material, human, and financial resources while considering the governance conditions required for responsible and sustainable use. Its contribution is empirical in consolidating a dispersed literature and distinguishing frequently represented application domains from claims of effectiveness, and conceptual in integrating AI-enabled analysis, decision support, resource allocation, governance safeguards, and intended outcomes into a context-sensitive framework for subsequent empirical investigation. The resulting framework is deliberately presented as a conceptual proposition rather than evidence that an operational AI allocation system has already been implemented or validated in Zambian schools. It provides a structured basis for subsequent empirical testing of how data quality, infrastructure, human capability, institutional readiness, governance, and contextual conditions interact with AI capabilities. The review therefore seeks to establish an evidence-informed foundation for future research, policy development, and educational administration concerning the responsible use of AI in the allocation of scarce educational resources.



1.1 Research Objective(s)

- i. systematically synthesise peer-reviewed literature published between 2021 and 2026 on AI applications relevant to material, human, and financial resource allocation in education;
- ii. identify the principal AI application domains and the cross-cutting governance and implementation conditions represented in the reviewed literature;
- iii. examine the implications of the international and African evidence base for AI-enabled resource allocation in Zambian schools; and
- iv. develop a conceptual framework that integrates AI-enabled analytical functions with governance safeguards and contextual conditions to guide future empirical research on sustainable resource allocation in Zambian education.

II. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 Resource-Based View

The Resource-Based View (RBV) provides a foundation for understanding how schools can derive sustained organisational value from resources that are valuable, rare, difficult to imitate, and organisationally embedded (Barney, 1991). In an AI-enabled resource-allocation environment, the relevant resource base extends beyond physical assets and personnel to include data, analytical capabilities, digital infrastructure, and organisational knowledge. From an educational perspective, RBV shifts attention from the mere acquisition of technology to the capacity of institutions to combine technology with human expertise and organisational processes. AI systems are therefore best understood as complementary capabilities whose value depends on the quality of the data, the competence of users, and the institutional arrangements through which recommendations are interpreted and acted upon. This interpretation is consistent with recent work emphasising the importance of human involvement and organisational capability in educational AI (Ifenthaler et al., 2024).

2.1.2 Dynamic Capabilities Theory

Dynamic Capabilities Theory complements RBV by explaining how organisations sense changes, seize opportunities, and reconfigure resources in response to changing environments (Teece et al., 1997). For schools, AI-enabled resource allocation may require continuous adjustment of staffing, infrastructure, budgets, data practices, and administrative routines. The theory is therefore useful for analysing whether institutions possess the adaptive capacity needed to turn analytical information into organisational action.

2.1.3 AI and Machine-Learning Perspectives

AI and machine-learning (ML) perspectives provide the technical logic through which data can be transformed into predictions, classifications, optimisation outputs, or decision-support information (Russell & Norvig, 2021). Recent reviews show that AIED research includes a wide range of analytical and predictive approaches, but also considerable variation in research contexts and methodological quality (Wang et al., 2024; Mustafa et al., 2024). In the present framework, AI and ML are consequently treated as analytical capabilities rather than as autonomous decision-makers. The three perspectives are complementary. RBV explains the strategic importance of resources and capabilities; Dynamic Capabilities Theory explains how institutions adapt and reconfigure those resources; and AI/ML perspectives explain how data can support prediction and decision-making. Together, they provide a defensible theoretical basis for a framework in which AI augments, rather than replaces, human judgement in sustainable resource allocation.

The resulting theoretical position is that sustainable AI-enabled allocation depends on the interaction of resources, organisational capabilities, analytical systems, and governance. The framework therefore places data and technology within a broader institutional system in which equity, transparency, accountability, and contextual fit are treated as design requirements rather than afterthoughts.

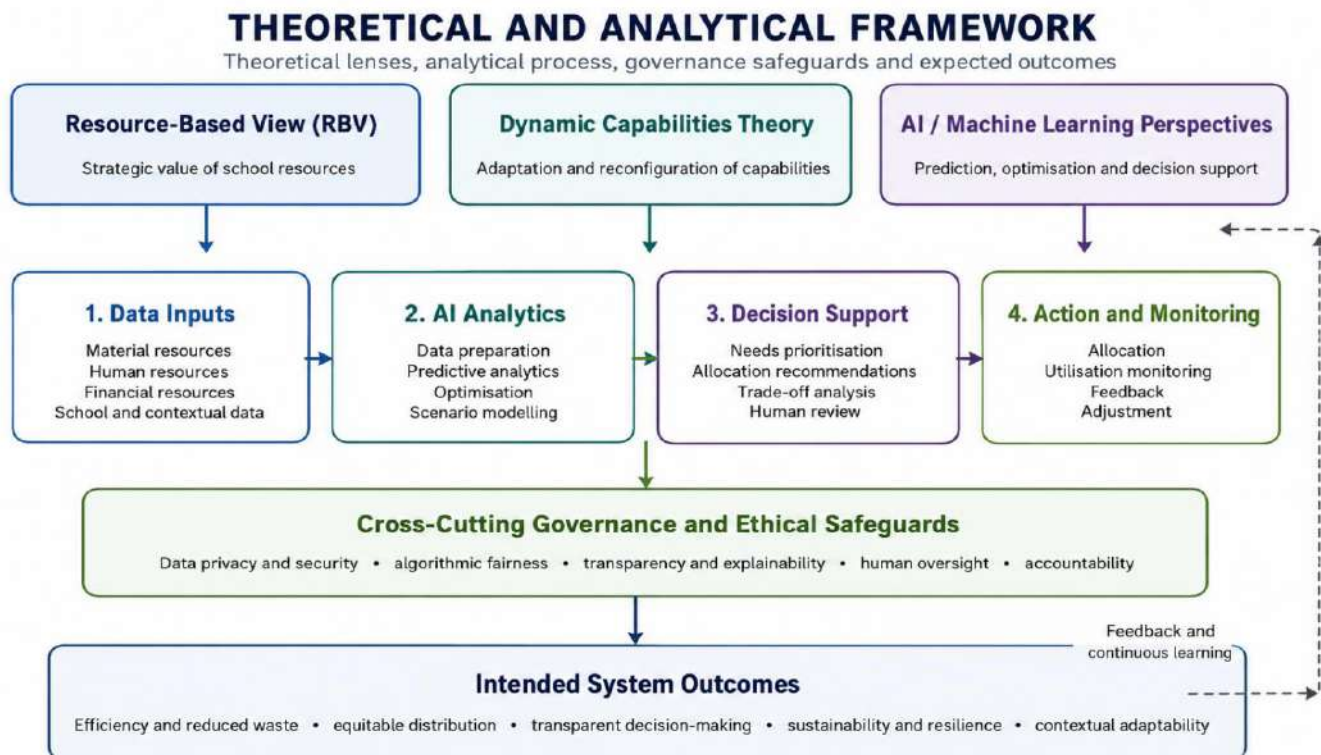


Figure 1
Theoretical and Analytical Framework

2.2 Empirical Review

Recent scholarship portrays AI in education as a heterogeneous field encompassing prediction, learning analytics, personalised learning, automated support, assessment, and administrative decision-making. A systematic review by Wang et al. (2024) found substantial diversity in applications, research designs, theoretical perspectives, and contexts, while Mustafa et al. (2024) identified a broad and rapidly expanding body of review literature. This breadth is important for resource allocation because the relevant evidence is distributed across several adjacent areas rather than concentrated in a single research stream. The literature also emphasises that AI adoption is inseparable from governance and human agency. Ifenthaler et al. (2024) argue for keeping humans in the loop when AI is introduced into education, while UNESCO (2023) identifies privacy, equity, transparency, safety, and capacity development as central conditions for responsible use. A recent systematic review of ethical risks similarly shows that concerns extend across technological, educational, and societal dimensions, including bias, privacy, accountability, and unequal access (Zhu et al., 2025). These findings are directly relevant to resource allocation because allocation decisions can affect access to teachers, infrastructure, learning materials, and financial support.

Teacher capability is another recurrent condition. Research on AI and machine learning in school education indicates that professional development remains uneven and that effective integration requires more than technical exposure (Sanusi et al., 2023). Evidence from Namibia further shows that teachers' perceived relevance of AI, attitudes, confidence, and perceptions of social value are associated with their intention to engage with AI in schools (Jatileni et al., 2024). Research on teacher education similarly identifies potential benefits for digital competence and teaching support while highlighting the need for institutional and professional support (Zhang & Zhang, 2024). Infrastructure and connectivity constitute a parallel constraint. AI-enabled systems depend on reliable electricity, devices, connectivity, data systems, and technical support. The OECD (2023) identifies digital infrastructure, governance, interoperability, and human competence as interdependent elements of a functioning digital education ecosystem. This is particularly salient in low-resource environments, where a technologically sophisticated allocation model may be unusable if the schools expected to supply data or act on recommendations lack the necessary infrastructure.

African evidence reinforces the importance of contextual adaptation. Studies involving educators in Namibia and several other African countries indicate that AI-related innovation is being introduced in environments where institutional capacity and access to technology vary substantially (Jatileni et al., 2024; Theodorio et al., 2024). Consequently, models developed in high-income settings cannot be assumed to transfer directly to Zambia. Local data structures, staffing patterns, infrastructure conditions, policy requirements, and professional practices must be treated

as part of the allocation problem rather than as peripheral implementation details. The Zambian policy environment is also moving toward greater digitalisation. The country's recent policy direction places increasing emphasis on digital infrastructure, data systems, capacity building, and the use of AI as part of wider digital transformation (Ministry of Education, 2025; Ministry of Technology and Science, 2024). These developments create a policy window for research on AI-supported educational management, but they also make evidence on feasibility, governance, and equity increasingly important. The present review therefore treats policy readiness as an enabling condition rather than as proof of implementation success. Taken together, the empirical literature suggests that the value of AI in education lies in its capacity to augment decision-making under appropriate conditions. The strongest defensible proposition is not that AI automatically improves resource allocation, but that AI can provide analytical capabilities that may improve planning and responsiveness when supported by reliable data, competent users, appropriate governance, and contextual adaptation (Ifenthaler et al., 2024; Wang et al., 2024; OECD, 2026). These findings provide the empirical basis for examining three principal resource-management applications in this review, predictive analytics, teacher allocation, and infrastructure monitoring. They also justify the inclusion of financial planning, policy simulation, governance, and human oversight within the conceptual framework.

2.3 Integrated Synthesis and Research Gap

The integrated synthesis consequently supports a framework in which data inputs feed AI-enabled analysis, analytical outputs inform decision support, decisions are implemented through human and institutional processes, and outcomes are monitored through governance and feedback mechanisms. Efficiency, equity, transparency, sustainability, and contextual adaptability are treated as linked objectives rather than as separate outcomes. This synthesis provides the conceptual bridge between the reviewed evidence and the framework proposed in this study, while leaving empirical validation of the framework for subsequent research in Zambian schools.

Context is equally important. The reviewed evidence is dominated by international studies, and the frequency of an application in the literature does not establish that the same application will have equivalent effects in Zambia. The Zambian education system includes differences in school location, infrastructure, staffing, connectivity, data quality, and administrative capacity that may affect both model performance and implementation. The appropriate contribution of an SLR is therefore to identify transferable principles and conditions while avoiding the assumption that models developed elsewhere can be transplanted without adaptation.

The synthesis also reveals an important asymmetry between technological capability and implementation capacity. AI systems may be capable of forecasting demand, identifying patterns, or generating allocation recommendations, but these capabilities depend on reliable data, appropriate infrastructure, professional competence, institutional authority, and governance arrangements. The barrier categories identified in the review therefore should not be treated as peripheral obstacles. They are part of the conditions that determine whether AI-generated information can become useful administrative action. This finding supports the use of Dynamic Capabilities Theory alongside the Resource-Based View, because sustainable value depends on both the resources available to institutions and their ability to reconfigure those resources as conditions change.

The empirical and theoretical literature converge on the view that AI-enabled resource allocation is best understood as a socio-technical capability rather than as an autonomous technological intervention. The coded evidence identifies predictive analytics, teacher allocation, and infrastructure monitoring as the three principal application domains, while the broader literature adds financial planning, policy simulation, and student support as potentially complementary functions. Their relevance to sustainable resource allocation lies in the possibility of connecting data about demand, resource availability, institutional conditions, and outcomes to decision processes that can be reviewed and adjusted by human decision-makers.

III. METHODOLOGY

This study employed a systematic literature review (SLR) to synthesise research on artificial intelligence applications relevant to sustainable resource allocation in education. The review approach was selected because the research question spans multiple application areas and requires transparent identification, screening, coding, and synthesis of published evidence. The review was structured and reported with reference to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 principles (Page et al., 2021).

The review targeted peer-reviewed journal articles published between 2021 and 2026 and searched Scopus, Web of Science, the Education Resources Information Center (ERIC), and Google Scholar. The time restriction was intended to capture the rapid development of contemporary AI applications while maintaining a manageable and clearly defined evidence base. The final coded corpus comprised 180 studies, represented in the results through the principal application categories identified during coding.

Table 1*Review Method and Analytical Workflow*

Review Element	Specification
Review design	Systematic literature review, structured and reported with reference to PRISMA 2020.
Databases	Scopus, Web of Science, ERIC, and Google Scholar.
Publication period	Peer-reviewed journal articles published between 2021 and 2026.
Eligibility focus	AI or machine-learning applications relevant to education and resource management or its enabling conditions.
Screening	Title and abstract screening followed by full-text assessment using the stated eligibility criteria.
Coding and synthesis	NVivo 14 for thematic coding; SPSS Statistics 29 for descriptive summaries.
Principal coded corpus	180 studies.
Principal application domains	Predictive analytics, teacher allocation, and infrastructure monitoring.

3.1 Review Design and Study Selection

The unit of analysis was the published study, not a human participant. Studies were eligible when they examined AI or machine-learning applications with clear relevance to education and resource management, including predictive analytics, teacher or workforce allocation, infrastructure or asset management, financial planning, decision support, or related governance functions. Studies were excluded when they were non-peer-reviewed, purely technical without educational relevance, or insufficiently transparent to support meaningful synthesis. The included literature covered a range of educational settings and levels, including school systems, K-12 education, teacher education, higher education, and system-level educational management. The review deliberately retained this breadth because relevant evidence on resource allocation is distributed across different educational contexts. Greater weight was given during interpretation to findings with clear implications for school-level or system-level resource management and to evidence from low-resource or African settings where available.

Each eligible article was treated as an independent unit of analysis. Data were extracted on publication characteristics, geographic context, methodological approach, AI application, resource domain, reported benefits, barriers, and implications for equity and sustainability. The coding structure was refined iteratively to distinguish the principal application areas from cross-cutting implementation conditions.

3.2 Software and Analytical Tools

Four software tools supported the review workflow. Zotero was used for reference management and duplicate handling; Rayyan was used to organise title, abstract, and full-text screening (Ouzzani et al., 2016); NVivo 14 was used for thematic coding and synthesis; and SPSS Statistics 29 was used for descriptive summaries of study characteristics and coded categories. These tools supported structured management of the evidence base but did not substitute for methodological judgement. Screening, extraction, coding, and interpretation remained human-led, and software outputs were checked against the underlying articles and the extraction framework.

3.3 Search and Selection Procedures

The search strategy followed PRISMA 2020 principles and used the four specified sources: Scopus, Web of Science, ERIC, and Google Scholar. Search terms combined concepts relating to artificial intelligence and machine learning with education, resource allocation, educational administration, sustainability, and, where appropriate, Zambia and comparable low-resource contexts. Boolean operators, including AND and OR, were used to combine synonyms and related terms. The strategy was designed to capture literature on predictive analytics, teacher allocation, infrastructure management, financial planning, decision support, and governance rather than restricting the review to a single AI technology. Retrieved records were organised in Zotero, where duplicate records were identified and removed, and screening was organised in Rayyan. Screening proceeded from title and abstract assessment to full-text assessment against the eligibility criteria.

Title and abstract screening excluded records that were clearly outside the educational and resource-management focus of the review. Full-text assessment was then used to determine whether the remaining studies satisfied the inclusion criteria and provided sufficient information for extraction and coding. The final evidence base comprised studies that were relevant to AI in education and to at least one dimension of resource management or its enabling conditions. The final coded corpus was 180 studies. Because the source dataset did not retain complete database-level retrieval counts and stage-specific exclusion totals, a numerical PRISMA flow diagram was not reconstructed retrospectively.

3.4 Data Analysis

The review used a convergent synthesis combining qualitative thematic coding with quantitative descriptive summaries. This approach was appropriate because the literature included conceptual, empirical, technical, and policy-oriented studies that varied substantially in design, measures, settings, and outcomes and therefore could not be pooled meaningfully in a conventional meta-analysis. Articles were coded in NVivo according to study context, methodological approach, AI application, resource domain, implementation barriers, reported outcomes, and relevance to the Zambian context. The coding process was iterative, with categories refined when new patterns emerged or when distinctions between application areas required clarification. Descriptive statistics were generated in SPSS to summarise publication characteristics and the frequency of coded categories. The principal application categories were predictive analytics, teacher allocation, and infrastructure monitoring. These frequencies are interpreted as characteristics of the reviewed literature, not as direct measures of AI effectiveness.

The synthesis was interpreted through the Resource-Based View, Dynamic Capabilities Theory, and AI/ML perspectives. The theoretical frameworks were used as analytical lenses for understanding resource value, organisational adaptation, and the role of computational methods in decision support rather than as statistical models. Coding and synthesis were reviewed iteratively against the extraction framework to improve consistency. No claim of independent double screening or inter-rater reliability is made because those procedures were not documented in the source review record. This limitation is addressed explicitly rather than retrospectively inferring a level of reliability that cannot be demonstrated.

3.5 Methodological Limitations

The review is limited by its focus on peer-reviewed journal articles published between 2021 and 2026. This improves temporal relevance but may exclude foundational work published earlier and relevant grey literature, policy documents, conference proceedings, and regional publications. The search was limited to Scopus, Web of Science, ERIC, and Google Scholar. Although these sources provide substantial coverage, they do not guarantee exhaustive retrieval of all relevant African or regional literature and therefore leave a residual risk of publication and database-selection bias.

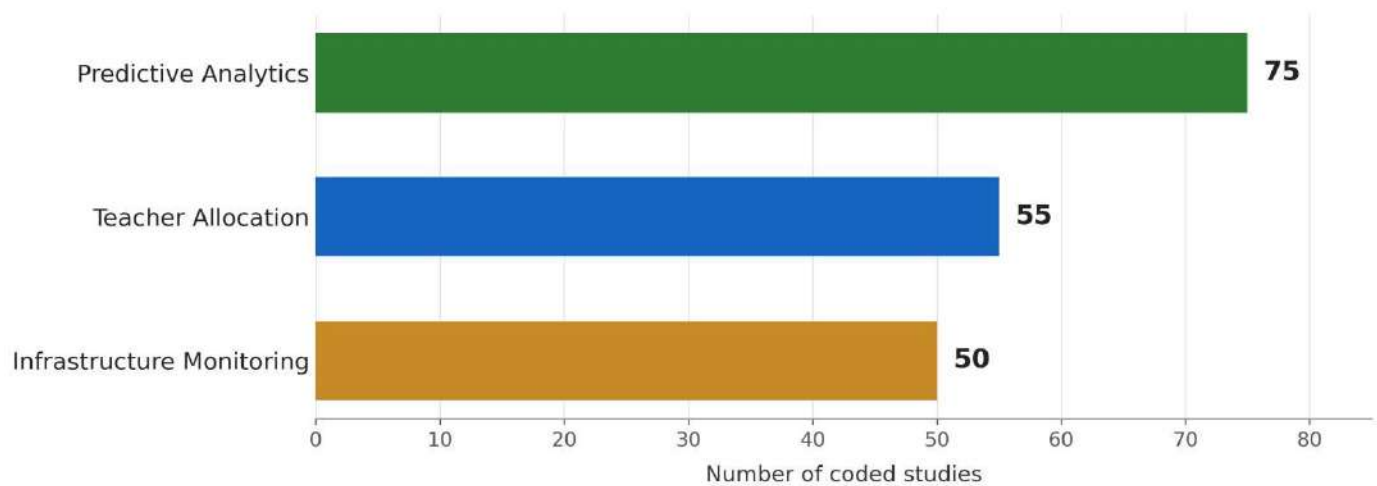
The coding and thematic synthesis required interpretive judgement. NVivo and SPSS supported organisation and descriptive analysis, but neither software eliminates subjectivity from category construction or interpretation. The heterogeneity of the evidence base also prevented a conventional meta-analysis. Finally, the application of global evidence to Zambia requires contextual caution. Differences in infrastructure, connectivity, funding, staffing, data quality, governance, and institutional capacity mean that the feasibility and effects of AI-enabled resource allocation must be empirically tested rather than assumed from evidence generated elsewhere.

IV. FINDINGS & DISCUSSION

4.1 Finding

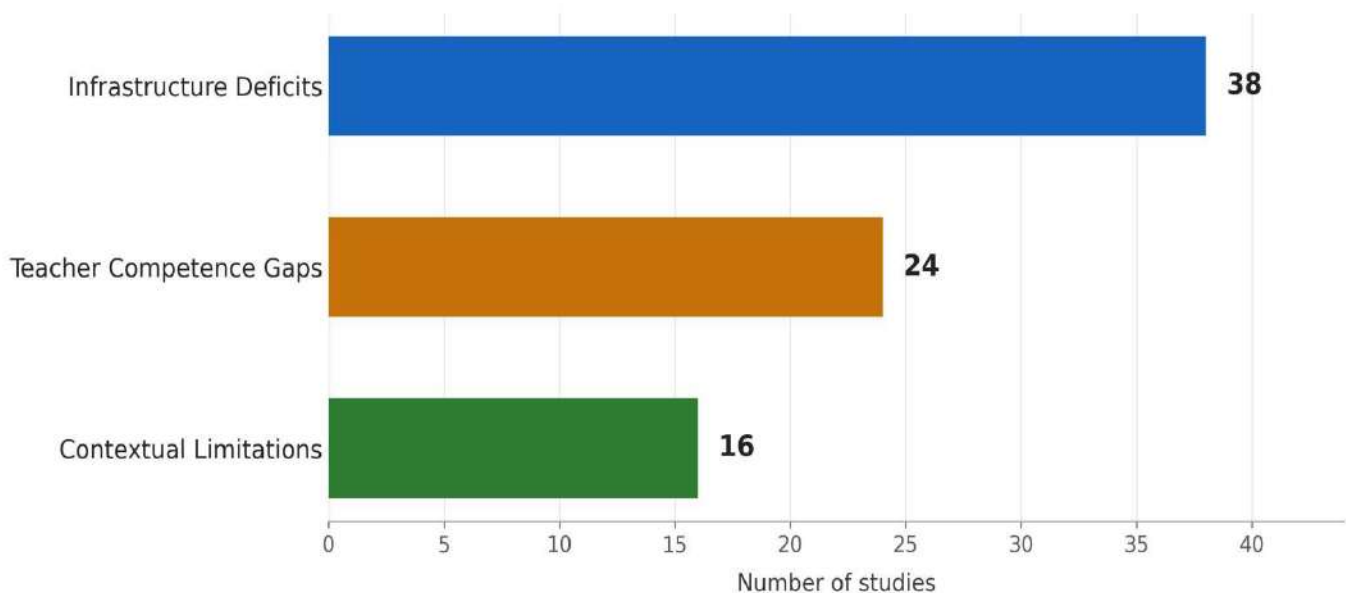
The final coded corpus comprised 180 studies. Across the literature, three principal application areas were most prominent: predictive analytics, teacher allocation, and infrastructure monitoring. Predictive analytics appeared in studies concerned with forecasting demand and planning; teacher allocation concerned the distribution and matching of human resources; and infrastructure monitoring concerned the tracking, maintenance, and accountability of physical and digital assets. These categories describe the distribution of research attention and should not be interpreted as direct estimates of intervention effectiveness. The distribution of applications varied by context. Studies from better-resourced settings more often examined advanced analytical and digital systems, while studies from low-resource settings more frequently addressed practical constraints, human-resource distribution, and access to infrastructure. These contextual differences are considered in the Discussion when assessing the transferability of international evidence to Zambia.

Cross-cutting governance issues were also prominent in the reviewed literature. Studies addressed data quality, transparency, accountability, privacy, professional capacity, and the authority to interpret and act on algorithmically generated recommendations (Ifenthaler et al., 2024; Zhu et al., 2025). These issues were treated as enabling conditions surrounding AI-supported resource management rather than as separate technical functions. In the principal application coding, predictive analytics accounted for 75 studies, teacher allocation for 55, and infrastructure monitoring for 50. Together, these three principal application categories represented the 180-study coded corpus. The frequencies were derived from the coded dataset and summarised using descriptive statistics; they describe the distribution of research attention rather than the effectiveness of the applications.

**Figure 2**

Applications of AI in Educational Resource Allocation: Coded Studies

Infrastructure deficits were the most frequently coded barrier, appearing in 38 studies. Reported concerns included unreliable connectivity, inadequate hardware, electricity constraints, and weak digital infrastructure. These conditions affect both the operation of AI systems and the quality of data available to them. Teacher competence gaps appeared in 24 studies. Reported concerns centred on the ability of educators and administrators to interpret AI outputs, recognise limitations, and integrate recommendations into professional practice. The literature also linked effective adoption to professional development and institutional support (Jatileni et al., 2024; Zhang & Zhang, 2024). Contextual limitations were identified in 16 studies. These included differences in infrastructure, funding, organisational practice, policy environments, and cultural or institutional expectations. The coded evidence therefore indicates that contextual adaptation is an important consideration when interpreting the feasibility of AI-enabled allocation in low-resource school systems. The barrier counts represent coded categories within the reviewed literature and are not interpreted as population estimates or prevalence measures.

**Figure 3**

Barriers to AI Adoption in Education: Non-Exclusive Coded Categories

Note. The three barrier categories are non-exclusive coding categories; a study could report more than one barrier. Their combined count ($38 + 24 + 16 = 78$) therefore does not need to equal the 180-study review corpus. The synthesis also identified four broad outcome categories: transparency and accountability, efficiency improvements, sustainability benefits, and professional development outcomes. The coded dataset associated AI applications with greater visibility of resource use and decision processes, potential efficiency gains, longer-term adaptability, and

professional learning. These are descriptive associations within the reviewed literature, not causal estimates attributable to AI across educational systems.

Transparency and accountability were associated with digital dashboards, automated records, and traceable decision processes. Efficiency was associated with forecasting, matching, monitoring, and reduced duplication. Sustainability was associated with the capacity to adjust allocation as conditions change, while professional development reflected the need for users to develop digital and analytical capabilities. Across these findings, the most defensible role of AI is as decision support embedded within governance structures. The potential benefits identified in the literature depend on data quality, user capability, institutional authority, and safeguards against bias and privacy harms (Ifenthaler et al., 2024; Zhu et al., 2025). The reported proportions were derived from the coded dataset and are presented as descriptive representations of the reviewed literature.

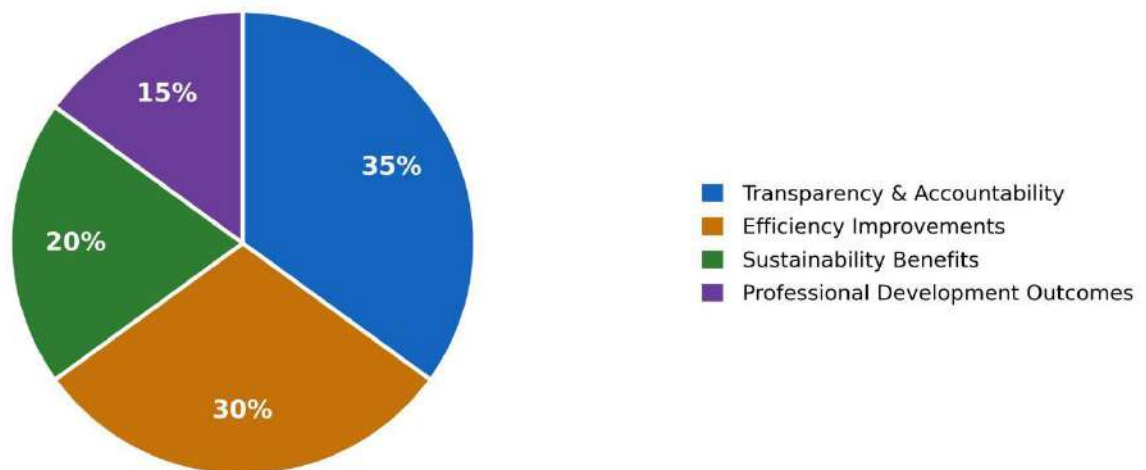


Figure 4
Positive Outcomes of AI in Education

When the global literature is interpreted through the Zambian context, three issues become particularly important. Predictive analytics could support enrolment and resource forecasting, but its usefulness would depend on the completeness and reliability of school records. Teacher allocation could provide analytical support for matching staffing with subject demand and school need, but would need to account for rural staffing constraints, professional rules, and human judgement. Infrastructure monitoring could strengthen visibility of assets and maintenance needs, but its feasibility would depend on electricity, connectivity, devices, data governance, and institutional capacity.

The central Zambian issue is therefore not simply whether AI can perform a particular analytical task. It is whether the surrounding information, infrastructure, governance, and human-capacity conditions are sufficient to make the resulting information usable and legitimate. A locally adapted approach should consequently treat data infrastructure, teacher and administrator competence, governance, and contextual constraints as integral components of the resource-allocation system. This interpretation is consistent with evidence from African educational settings and international guidance on equitable and human-centred AI adoption (Jatileni et al., 2024; Theodorio et al., 2024; UNESCO, 2023; OECD, 2026). The synthesis therefore positions AI as a potential source of better-informed resource management while recognising that implementation effectiveness remains an empirical question for Zambia.

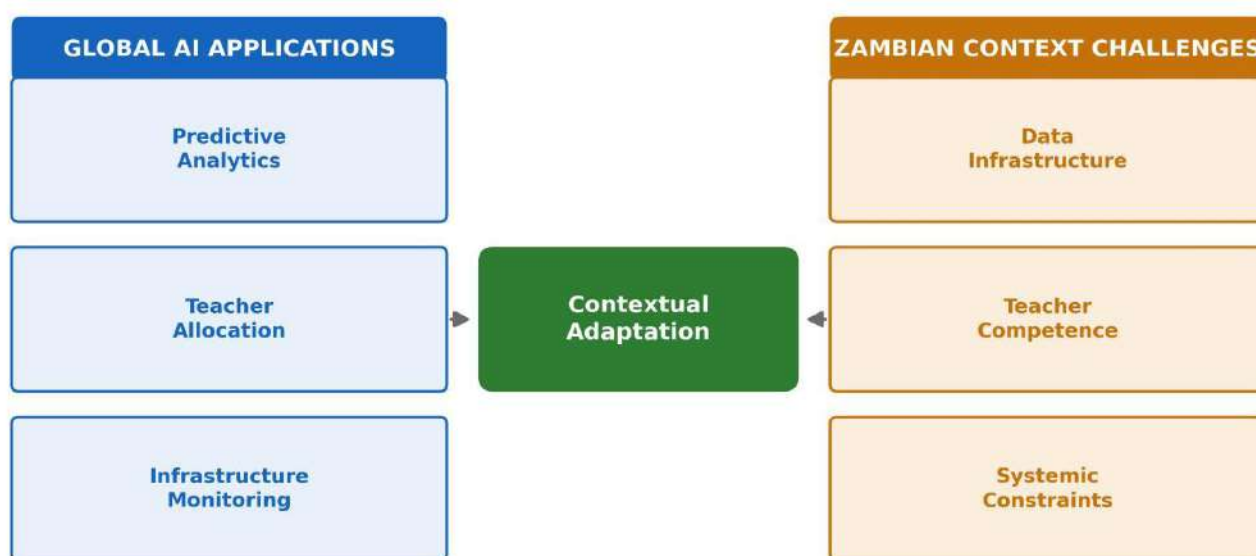


Figure 5
Synthesis of Global Findings and Zambian Context

The review identifies a consistent distinction between AI capability and implementation effectiveness. Predictive analytics, teacher allocation, and infrastructure monitoring are the three principal application domains in the coded corpus, but their practical value depends on data quality, infrastructure, human capability, governance, and contextual fit. The evidence therefore supports a conditional interpretation: AI can augment resource-management decisions, but the reviewed literature does not justify treating AI as an automatic solution to inefficiency or inequity (Wang et al., 2024; Mustafa et al., 2024; Ifenthaler et al., 2024; OECD, 2026).

Table 2
Coded Literature Findings Across the Three Principal AI Application Areas

Area	Application	Description	Coded Literature and Zambian Implications
Area 1	Predictive Analytics	Forecasting enrolment and resource needs	75 coded studies. Forecasting potential; Zambia requires reliable records, digitisation, and analytical capacity.
Area 2	Teacher Allocation	Supporting teacher distribution	55 coded studies. Staffing support; Zambia requires attention to rural shortages, professional rules, and human oversight.
Area 3	Infrastructure Monitoring	Tracking assets and maintenance	50 coded studies. Greater asset visibility; Zambia requires electricity, connectivity, data quality, and institutional capacity.

Table 2 summarises the three principal application areas identified in the review. The coded literature suggests potential contributions to forecasting, staffing decisions, and infrastructure oversight, while the corresponding Zambian implications remain contingent on local data, infrastructure, institutional capacity, and governance. The table distinguishes literature-derived evidence from contextual interpretation rather than presenting global studies as primary data from Zambia. Predictive analytics is relevant because resource planning requires estimates of future demand. Recent AIED reviews document growing use of data-driven and predictive approaches across education (Wang et al., 2024; Ikram et al., 2026). For resource allocation, such approaches could support forecasting of enrolment, staffing requirements, infrastructure needs, and expenditure patterns. Their usefulness, however, depends on the quality and representativeness of the underlying data, and model outputs require human interpretation before they are translated into allocation decisions.

For Zambia, predictive applications may be useful where reliable historical and administrative data are available. Feasibility is likely to be more limited where records remain fragmented, incomplete, or predominantly manual. Data infrastructure and analytical capacity should therefore be treated as prerequisites for meaningful deployment rather than as secondary implementation issues. Teacher allocation is another important application because the distribution of teachers across schools affects educational opportunity. AI-supported allocation could assist administrators by combining enrolment, subject demand, qualifications, workload, geography, and other



constraints. Evidence from African contexts indicates that AI adoption depends strongly on teacher readiness and institutional conditions (Jatileni et al., 2024; Theodorio et al., 2024). Any allocation model should therefore function as decision support subject to professional and administrative oversight, rather than as an autonomous mechanism for assigning teachers.

For Zambia, this distinction is especially important because staffing decisions are embedded within professional, administrative, geographic, and policy considerations. An AI model could identify potential mismatches or simulate alternative deployment options, but final decisions would require transparent criteria, human review, and mechanisms for contesting or correcting recommendations. Infrastructure monitoring provides a third application area. AI and related analytical systems can support asset registers, maintenance forecasting, utilisation monitoring, and anomaly detection. Such functions may be particularly relevant where schools manage distributed assets and administrative visibility is limited. Nevertheless, infrastructure monitoring requires reliable data capture and connectivity and should be integrated with accountability processes so that detected problems lead to action rather than simply generating additional information.

The three application areas converge on a broader point: analytical capability alone is insufficient. The conceptual framework developed from the review combines AI-enabled functions with governance and contextual safeguards, reflecting the literature's emphasis on human-centred, transparent, and locally responsive educational AI (Ifenthaler et al., 2024; UNESCO, 2023; Zhu et al., 2025). The synthesis of predictive analytics, teacher allocation, infrastructure monitoring, financial planning, policy simulation, and student support provides the basis for a conceptual framework for sustainable resource allocation in Zambia. The framework is organised around contextual inputs, AI-enabled analytical functions, governance safeguards, and intended system outcomes. The framework links four contextual input domains, material, human, financial, and contextual resources, to analytical functions that include predictive analytics, teacher allocation, infrastructure monitoring, and financial and policy planning. This arrangement reflects the review finding that resource allocation cannot be separated from the data and institutional conditions in which allocation decisions are made.

The first layer represents the resources and contextual data required by an allocation system. The second represents analytical functions that transform those inputs into forecasts, recommendations, monitoring information, and scenarios. Decision-making remains a human and institutional process rather than an automated endpoint. A cross-cutting governance layer addresses data protection, fairness, transparency, human oversight, accountability, and stakeholder engagement. The final layer identifies intended outcomes of efficiency, equity, transparency, and sustainability. These outcomes are propositions for empirical evaluation, not claims of demonstrated effects in Zambia.

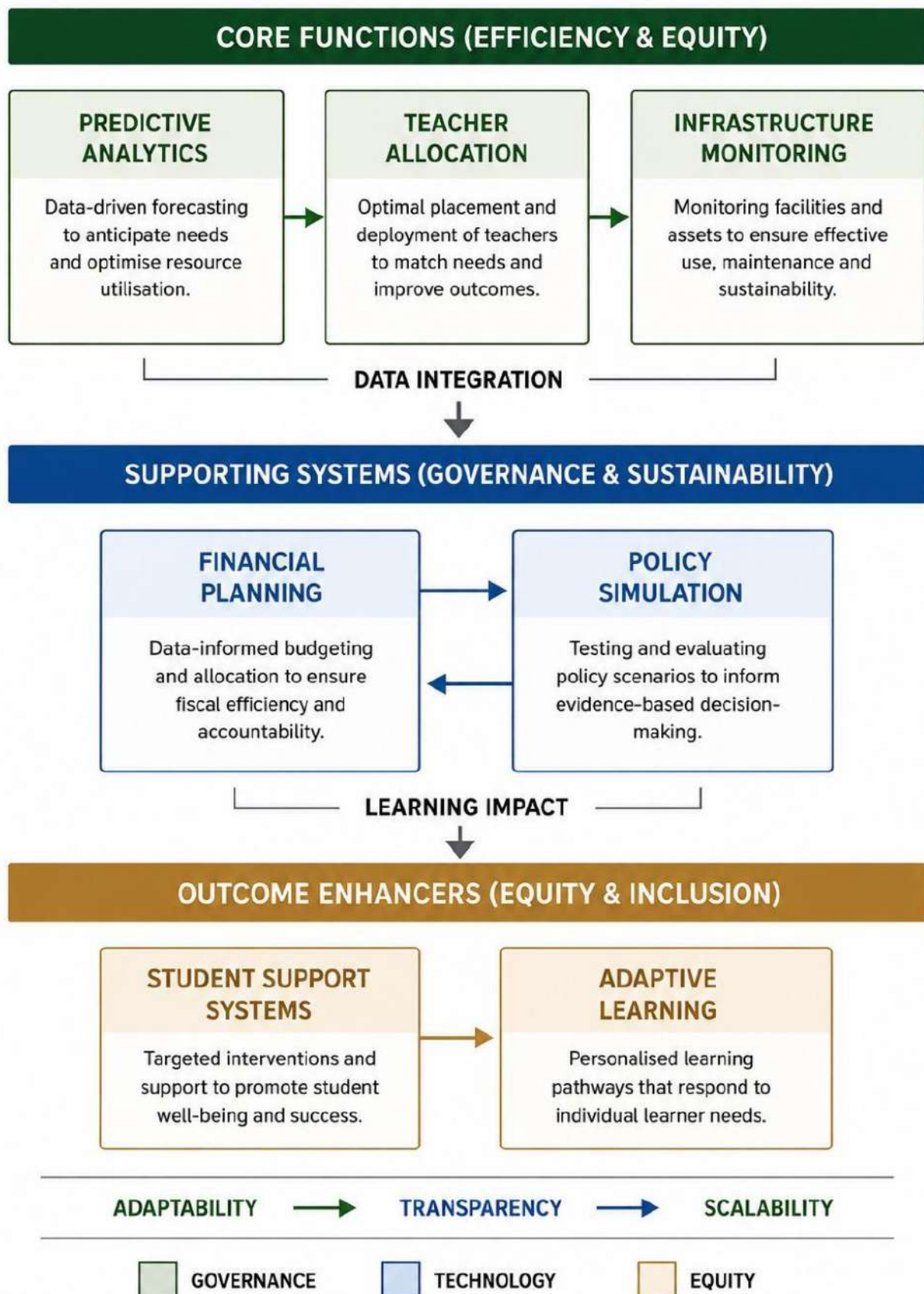


Figure 6
Conceptual Framework for Sustainable Resource Allocation in Zambian Education

Each major framework component can be traced to a recurring evidence pattern in the review: data inputs reflect the literature on data and infrastructure constraints; AI analytics reflect the prominence of predictive and

analytical applications; decision support reflects the emphasis on human interpretation and administrative use; action and monitoring reflect the need to connect information with resource-management processes; and the governance layer reflects recurring concerns about fairness, privacy, transparency, accountability, and human oversight. The framework is therefore derived from the synthesis rather than presented as an independent technological prescription. In the Zambian context, the framework serves as a conceptual guide for future empirical testing. Its central proposition is that sustainable allocation requires the integration of analytical capability with data infrastructure, human capacity, governance, and contextual adaptation. AI is consequently positioned as an augmenting capability within educational administration, not as a substitute for institutional judgement. The framework also identifies three supporting domains that can extend resource-allocation capability: financial planning, policy simulation, and student support. These domains are included because resource allocation ultimately affects the conditions under which teaching, learning, and institutional performance occur.

Financial planning could use predictive and anomaly-detection methods to support expenditure monitoring, forecasting, and scenario analysis. Such applications may strengthen accountability, but their usefulness would depend on the completeness, consistency, and governance of financial data.

Policy simulation could allow administrators to compare alternative allocation strategies before implementation. For example, a model could estimate the resource implications of different teacher-deployment or infrastructure-investment scenarios. Such simulations would inform judgement rather than determine policy automatically.

Student support systems may also generate information relevant to resource planning, including patterns of participation, learning needs, or risk. Adaptive learning is treated in the framework as a supporting educational application rather than a core allocation function. Recent literature on AI and personalised learning indicates growing interest in these applications, although their educational and ethical implications require careful evaluation (Ikram et al., 2026; Zhu et al., 2025). Collectively, these supporting domains connect resource allocation with governance, institutional learning, and educational outcomes while preserving the distinction between conceptual potential and empirically demonstrated effectiveness.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

In relation to the research objectives set out in the introduction, this systematic literature review identified predictive analytics, teacher allocation, and infrastructure monitoring as the three principal AI application areas relevant to educational resource management in the reviewed corpus. It also identified financial planning, policy simulation, governance, and student support as complementary domains. The evidence indicates meaningful potential for AI-enabled decision support, but it does not establish that AI will automatically improve efficiency, equity, or sustainability across educational systems. The proposed conceptual framework responds to this evidence by linking contextual inputs and AI-enabled analytical functions with governance safeguards and intended outcomes. It emphasises human oversight, transparency, accountability, contextual adaptation, and continuous learning. These features are particularly important for Zambia because infrastructure, data quality, professional capacity, and institutional readiness vary across educational settings.

The principal contribution of the review is conceptual. It provides a structured basis for examining how AI could support sustainable resource allocation in Zambian education while identifying the conditions that must be addressed before implementation can be considered defensible. Future empirical research should test the framework using real administrative and school-level data and should evaluate predictive performance alongside fairness, usability, institutional legitimacy, and resource outcomes. AI should therefore be understood neither as a substitute for educational administration nor as a technological end in itself. Its most defensible role is as an analytical capability embedded within a transparent, human-centred, and contextually responsive resource-management system.

5.2 Recommendations

The review supports several priorities for the responsible development and future testing of AI-enabled resource allocation in Zambia. First, teacher and administrator preparation should be strengthened. Professional development should include AI literacy, data interpretation, digital ethics, and practical use of decision-support systems. Evidence from African and international settings indicates that confidence, perceived relevance, and professional support influence readiness to engage with AI. Second, infrastructure and data systems should be strengthened before large-scale deployment. Reliable electricity, connectivity, devices, interoperable records, secure data platforms, and technical support are prerequisites for meaningful AI-enabled administration. Investment should explicitly address disparities between better-connected and underserved schools.

Third, financial and resource-management systems should be progressively digitised and standardised so that AI applications can operate on consistent and auditable data. AI-based budgeting or anomaly detection should be introduced as decision-support functions subject to established financial controls and human review. Fourth, governance arrangements should define responsibilities for data protection, algorithmic fairness, transparency, explainability, accountability, and appeal. The human-centred approach advocated by UNESCO and the OECD is particularly relevant where AI outputs may influence the distribution of scarce educational resources. Fifth, future empirical studies should test the proposed framework in real school settings before claims of effectiveness are made. Pilot studies should examine data quality, predictive performance, usability, fairness, institutional acceptance, and resource outcomes across urban, peri-urban, and rural contexts. These recommendations position AI as one component of a broader reform programme combining human capacity, infrastructure, data governance, financial accountability, and adaptive institutional practice. This approach is more consistent with the evidence than technology-first implementation.

Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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