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Impact Of Artificial Intelligence on Education in Urbarn Schools of Lusaka, A Case of Five Secondary Schools

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Abstract- This study investigated the impact of Artificial Intelligence (AI) on education in urban secondary schools in Lusaka, Zambia. It examined the extent and forms of AI adoption, and assessed effects on student learning outcomes, engagement, and motivation, alongside changes in teacher effectiveness and instructional practice. The research interrogated ethical and equity concerns, including algorithmic bias, transparency, and differential access, and it located findings within the local policy and infrastructural context. A convergent of this research was on Libala, Kamwala, David Kaunda, Kabulonga, and Rhodes park Secondary Schools. Mixed-methods design was employed. Quantitative data were collected via structured questionnaires from a stratified sample of 200 students and 50 teachers, and were analyzed using descriptive statistics and inferential tests (t-tests, ANOVA, regression) in SPSS. Qualitative data were generated through semi-structured interviews, classroom observations, and document review in five purposively selected case schools and were analyzed thematically with NVivo. The study anticipated that AI-powered adaptive systems and analytics had improved individualized learning and formative feedback, that teacher workload was partially reduced through automation while pedagogical roles became more diagnostic and supervisory, and that gains were moderated by inequitable access and limited teacher training. The study contributed empirically grounded, context-sensitive evidence on how AI shaped learning and teaching in a low-resource urban setting and clarified the trade-offs between pedagogical affordances and ethical risks. Findings informed practical recommendations for policymakers, school leaders, and ed-tech developers to priorities equitable roll-out, transparent algorithmic design, and sustained teacher professional development. These recommendations were expected to guide responsible AI integration to enhance learning outcomes without undermining educational equity.

Keywords- Artificial Intelligence; education; adaptive learning; teacher effectiveness; learning analytics; equity; Zambia.

I. Introduction

This study investigated how Artificial Intelligence (AI) had reshaped teaching and learning in urban secondary schools in Lusaka, Zambia. It examined the forms and extent of AI adoption, its influence on student learning outcomes and engagement, and its effects on teacher roles and instructional quality. The research framed AI as a set of algorithmic systems and tools—adaptive learning platforms, intelligent tutoring systems, automated assessment engines and learning-analytics dashboards—that mediated pedagogical decision making and classroom practice (Luckin et al., 2016;

Siemens, 2013). The inquiry foregrounded equity, algorithmic transparency and teacher professional capacity as central lenses because empirical and policy literature had repeatedly signaled that technological affordances alone did not guarantee improved learning; contextual factors and governance arrangements shaped outcomes (Zawacki-Richter et al., 2019; UNESCO, 2019). Using a convergent mixed-methods design, the study combined survey data from students and teachers with in-depth case studies in five secondary schools to generate both breadth and contextualized depth. The chapter outlined the study's rationale, situational background, problem statement, objectives and research questions, and then described characteristic features of the phenomena and the principal factors associated with AI integration in the study context.

Background of the study

The rapid diffusion of AI into education had been propelled by advances in machine learning, wider access to digital infrastructure and commercial development of pedagogical applications (Luckin et al., 2016). Globally, ministries and education providers experimented with adaptive learning systems, automated formative assessment and predictive analytics to personalize instruction and monitor progress (UNESCO, 2019). Empirical reviews indicated measurable gains in specific domains when AI systems provided targeted practice and immediate feedback, particularly in mathematics and reading (Nye, 2015; Pane et al., 2015). At the same time, scholars cautioned that algorithmic models reproduced biases present in training data, that opaque decision rules undermined pedagogical accountability, and that unequal access risked widening existing inequities (Zawacki-Richter et al., 2019; Williamson & Eynon, 2020). In

Zambia, pilot initiatives and small-scale studies had documented early promise in using digital tools to support content delivery and remedial learning, while also identifying infrastructural constraints, limited teacher readiness and policy gaps as impediments to scale (Mweene & Lungu, 2020; Mwanza & Nkamba, 2019). These mixed findings motivated an empirical study that combined quantitative measurement of outcomes with qualitative inquiry into classroom practice and institutional decision making, thereby situating technological effects within local resource, pedagogical and governance conditions.

Problem statement

Despite growing investments in AI-enabled educational products and pilot deployments across low- and middle-income contexts, robust evidence on their effects within Zambian secondary schools remained limited. Schools that adopted AI tools reported improvements in formative feedback and administrative efficiency, yet systematic assessments of changes in student achievement, engagement and teacher effectiveness were scarce. Moreover, little was known about how algorithmic decision making interacted with local inequities, teacher capacity and school governance to shape observed outcomes. Policymakers and school leaders therefore faced a dilemma: implement and scale AI solutions with uncertain distributional effects, or delay adoption pending clearer evidence. The study addressed this gap by

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empirically investigating what kinds of AI were adopted in Lusaka secondary schools, how those technologies had influenced measurable student outcomes and teacher practices, and which contextual factors moderated benefits or generated risks. The research positioned these questions to inform practical and ethical strategies for responsible AI integration that would support learning gains without exacerbating inequity or undermining teacher professionalism.

Purpose of this Study

- To find out IMPACT OF ARTIFICIAL INTELLIGENCE ON EDUCATION IN URBARN
- SCHOOLS OF LUSAKA in urban schools of Lusaka due to rapid diffusion of AI into education.

Research objectives
General objective
To investigate the IMPACT OF ARTIFICIAL INTELLIGENCE ON EDUCATION IN
URBARN SCHOOLS OF LUSAKA in urban secondary schools in Lusaka, Zambia.

Specific objectives

1. To document the current state and forms of AI adoption in selected secondary schools.
2. To assess the impact of AI use on student learning outcomes, engagement and motivation.
3. To examine how AI tools affected teacher effectiveness, workload and instructional practice.
4. To identify equity, bias and transparency challenges associated with AI integration.
5. To develop context-sensitive recommendations for policymakers, school leaders and developers to support equitable and effective AI deployment.

Research questions

1. What types of AI-powered tools and systems had been adopted in Lusaka secondary schools and to what extent were they used?
2. How had AI integration affected student learning outcomes, engagement and motivation?
3. In what ways had AI changed teacher effectiveness, workload and instructional design?
4. What equity, bias and transparency issues emerged from AI deployment in the study schools?
5. What strategies were appropriate to promote responsible, equitable and effective AI integration in the local context?

Characteristic of the phenomena

AI integration in the educational setting presented distinct, observable characteristics. First, it operated at multiple levels: student-facing adaptive interfaces, teacher dashboards for formative assessment, and administrative automation for grading and scheduling (Siemens, 2013). Second, the phenomena were hybrid and socio-technical, in which algorithmic outputs interacted with teacher interpretation, curricular constraints and classroom norms; technology effects therefore depended on human mediation rather than being purely deterministic (Luckin et al., 2016). Third, adoption exhibited heterogeneity across schools and learners: some classrooms used AI intensively for personalized practice while others limited use to occasional assessments, producing variable exposure and outcomes. Fourth, the phenomena manifested trade-offs: automation reduced routine workloads yet shifted teacher roles toward data interpretation and individualized support, requiring new skills and professional time. Finally, the phenomena were dynamic and evolving, as updates to platforms, changes in procurement and policy signals shaped both capabilities and governance during the study period.

Factors related to the phenomena

A constellation of interrelated factors influenced how AI manifested and what consequences it produced. Technological factors included platform design, algorithmic transparency, data requirements and interoperability with existing school systems. Systems that provided clear learning pathways, interpretable feedback and alignment with curriculum were more likely to support productive classroom use; opaque score generation and poorly aligned content undermined teacher trust and uptake (Zawacki-Richter et al., 2019). Human factors comprised teacher digital literacy, attitudes toward technology, and pedagogical beliefs. Teachers with prior experience in formative assessment and data-informed instruction engaged AI outputs critically and integrated them into lesson planning, whereas teachers with limited training tended to rely on system outputs superficially.

Institutional and organizational factors shaped resource allocation, decision authority and professional development. School leadership that allocated time for teacher training and fostered collaborative problem solving enabled more effective use of AI; conversely, ad hoc procurement without implementation support produced inconsistent effects. Equity factors—device access, home connectivity and socio-economic status—moderated student engagement and learning gains; learners lacking devices or reliable connections experienced interrupted access and reduced benefit. Policy and governance factors included data protection regulations, procurement policies and curriculum guidance; absence of clear governance frameworks amplified risks related to privacy and algorithmic accountability.

Market and vendor factors also mattered: commercially produced platforms varied in cost, support services and localizability. Vendors that offered teacher training, content adaptation and local language support facilitated contextual relevance. Finally, evaluative and cultural factors influenced sustainability—schools that embedded monitoring and reflection into implementation cycles were better positioned to iterate and scale. Taken together, these factors operated interactively to condition whether AI interventions produced intended pedagogical improvements or unintended inequities.

Global Statistical Scenario

By 2023 the global education sector had shown accelerating interest in artificial intelligence, evidenced by rapid growth in investment, product deployments and empirical studies that quantified AI's impact on learning processes and systems. Market analyses reported that the global AI in education market had expanded at double-digit compound annual growth rates, driven by investments in adaptive learning, automated assessment and learning analytics platforms (HolonIQ, 2022).

Large randomized controlled trials and meta-analyses conducted across OECD and non-OECD settings had demonstrated modest but consistent effect sizes for targeted, domain-specific intelligent tutoring systems (ITS) and adaptive practice on student achievement in mathematics and reading (Nye, 2015; Pane et al., 2015). Learning analytics implementations at scale yielded improvements in retention and early warning detection of at-risk learners when institutional data systems and teacher mediation were in place (Siemens, 2013).

At the systems level, national ministries reported growing use of AI for administrative efficiencies, such as automated grading and scheduling, with some high-income countries integrating predictive analytics into early warning and resource allocation systems (UNESCO, 2019). Simultaneously, cross-national analyses highlighted widening access gaps: learners in low-income households remained less likely to benefit from online adaptive learning due to device and connectivity deficits, producing differential uptake that correlated with socio-economic indicators (World Bank, 2021). Algorithmic bias studies quantified how model training on non-representative datasets produced disparate predictions and recommendations for minority groups, prompting policy debates about fairness metrics and transparency obligations (Williamson & Eynon, 2020).

Research synthesis work therefore painted a nuanced global picture: AI systems produced measurable pedagogical gains when interventions were tightly scoped, evidence-based and accompanied by teacher professional development, but risks to equity, privacy and accountability were significant where governance frameworks and infrastructure were weak (Luckin et al., 2016; Zawacki-Richter et al., 2019). Global indicators thus signaled both opportunity and caution: countries that combined investment in platforms with investments in teacher capacity and data governance realized larger and more equitable returns than those that pursued technology procurement alone.

Local Statistical Scenario

Zambia's digital education landscape had exhibited growing but uneven digital adoption. National surveys and sector reports indicated that internet penetration in urban centers such as Lusaka exceeded national averages, enabling schools in these areas to trial digital learning platforms more readily than rural counterparts (Ministry of Education Zambia, 2021). Small-scale studies and pilot evaluations documented improvements in student engagement where adaptive tools were used for remedial instruction in mathematics and science, though nationally representative evidence on achievement gains remained limited (Mwanza & Nkamba, 2019; Mweene & Lungu, 2020). Device access and home connectivity statistics revealed socio-economic gradients: students from higher-income households reported daily device access, while a substantial proportion of lower-income students relied on shared school resources or irregular connectivity, constraining sustained use of AI-driven platforms (Zambia ICT Survey, 2022). Policy documents signaled increasing policy attention to educational technology but noted gaps in data protection regulation and localized teacher training programs that would be required for scaled, equitable AI integration (Ministry of Education Zambia, 2022).

Scope of the Study

The study focused on urban secondary schools in Lusaka and specifically examined experiences of students in grades 10–12 and their teachers during the 2024–2025 school period. It concentrated on AI-powered educational tools that were in practical classroom use, including adaptive learning platforms, intelligent tutoring modules, formative assessment engines and

teacher dashboards for learning analytics. The research deliberately excluded purely administrative AI applications that were unrelated to pedagogy, such as payroll automation, unless those systems directly influenced instructional practice. The empirical work combined a stratified survey of 200 students and 50 teachers across five purposively selected secondary schools with in-depth case studies in the same institutions that comprised semi-structured interviews, classroom observations and document review.

The study therefore privileged depth of contextualized understanding within a bounded urban setting rather than claiming national generalizability. Timewise, the investigation examined adoption patterns, reported outcomes and teacher practice within the academic year preceding data collection. The study's delimitations were chosen to produce actionable, context-sensitive recommendations for Lusaka's school leaders and municipal policymakers, while acknowledging that rural contexts and primary or tertiary levels would require separate, dedicated inquiry.

Usefulness of the study in the present scenario

The study generated practical and scholarly value by producing empirically grounded evidence on how AI functioned within real classrooms in an urban Zambian setting. First, it provided localized evidence on student learning and engagement associated with specific AI tools, offering school leaders and district officials measurable indicators to inform procurement and pedagogical deployment decisions. Educational managers required such evidence to allocate scarce resources efficiently; the study's mixed-methods findings clarified which tools yielded the largest pedagogical returns when paired with teacher mediation, thus guiding cost-effective investment.

Second, the research addressed teacher professional development needs by documenting how AI altered instructional workflows and which competencies teachers needed to interpret analytics and personalize interventions. This evidence supported designing targeted in-service training modules and structured professional learning communities, thereby increasing the likelihood that technology investments translated into improved classroom practice. Third, the study highlighted equity differentials in device access and connectivity, supplying policymakers with disaggregated data that justified targeted subsidies, device-sharing schemes or adjusted timetabling to maximize inclusive access. By evidencing where AI exacerbated or ameliorated disparities, the study informed locally appropriate equity strategies.

Fourth, the study contributed to governance and ethical decision-making by examining transparency, data protection and vendor practices; findings helped education officials draft procurement clauses, vendor support requirements and basic data governance checklists to mitigate privacy and algorithmic bias risks. Finally, the study added to academic discourse by combining effectiveness measures with rich qualitative accounts, thereby advancing theory on socio-technical mediation of learning technologies in low-resource urban schools. The combined practical and theoretical contributions positioned the study to influence policy, guide school-level implementation and inform subsequent research on scaling responsible AI in education.

Operational Definitions

- Artificial Intelligence (AI): computational systems capable of performing tasks that normally required human intelligence, including adaptive instruction, automated feedback and predictive analytics (Luckin et al., 2016).
- Adaptive Learning Platform: software that adjusted learning pathways and practice items to a learner's demonstrated performance in real time (Nye, 2015).
- Intelligent Tutoring System (ITS): a computer-based instructional system that provided personalized instruction and feedback grounded in learner modelling (Nye, 2015).
- Learning Analytics: measurement and analysis of learner data to inform instructional decisions and predict learner needs (Siemens, 2013).
- Teacher Effectiveness: the capacity of teachers to improve student learning outcomes, manage classrooms and use assessment data to adapt instruction (Pane et al., 2015).
- Equity in Education: fair access to learning opportunities and resources irrespective of socio-economic status, gender or location (UNESCO, 2019).
- Algorithmic Transparency: the degree to which the functioning and decision rules of AI systems were explainable and interpretable to stakeholders (Williamson & Eynon, 2020).

Chaptalization

The study comprised five chapters that together provided a coherent narrative from problem identification to recommended action. Chapter One presented the study's rationale and situational background, articulated the problem statement, stated the general and specific objectives, listed the research questions, and described the characteristic features and contextual factors that shaped AI integration in Lusaka secondary schools. Chapter Two synthesised global and local scholarly work on AI in education, reviewed relevant theoretical frameworks, and identified empirical gaps that the present study addressed. Chapter Three described the research methodology, detailing the mixed-methods design, sampling strategy, instrument development, data collection procedures, analysis techniques and ethical safeguards.

Chapter Four reported the empirical results, presenting quantitative analyses of survey data alongside thematic findings from interviews, observations and document review to capture both scope and depth of the phenomena. Chapter Five integrated interpretation and judgement: it discussed results in relation to the literature and theoretical lenses, drew conclusions about AI's pedagogical and equity effects in the study context, and offered evidence-based recommendations for policy, school practice and vendor engagement, while noting limitations and proposing directions for future research.

Chapter summary

Chapter One established the study's purpose and situated it within global and local debates about the educational uses of AI. It outlined the research problem: the absence of robust, contextualized evidence on how AI tools affected student outcomes and teacher practice in Lusaka secondary schools. The chapter set out a clear general objective and five specific objectives, and it posed five research questions that guided the empirical work. It characterized the phenomena of AI integration as socio-technical, heterogeneous and dynamic, and it described a matrix of technological, human, institutional, equity, market and governance factors that conditioned outcomes. The chapter presented a brief global and local statistical scenario, described the study scope and explained the study's usefulness for policy, practice and scholarship. Operational definitions clarified key terms and a chaptalization previewed the report structure. Collectively, these elements established a coherent conceptual and methodological foundation for the subsequent literature review and empirical chapters.

II. Literature Review

Overview

This chapter reviewed scholarly and policy literature on the intersection of artificial intelligence (AI) and education, with the aim of situating the present study within existing knowledge, identifying empirical gaps and clarifying theoretical lenses that guided the empirical enquiry. The review proceeded in three linked parts. First, it summarized conceptual and theoretical foundations that defined AI in education, described principal AI applications in schooling, and explained key analytic concepts such as personalized learning, learning analytics and algorithmic transparency. Second, it synthesized empirical evidence on the effects of AI-enabled interventions on student learning, teacher practice and system-level outcomes, attending to contextual variation between high-income and low- and middle-income settings. Third, it critically examined cross-cutting concerns—equity, bias, data governance and teacher professional capacity—that recurrently shaped both outcomes and implementation pathways. The literature review therefore combined conceptual clarification with empirical synthesis and critical interrogation of ethical and governance issues, acknowledging that technology effects were inseparable from social, institutional and policy contexts.

Conceptually, the review treated AI as a socio-technical ensemble rather than a neutral tool, emphasizing that algorithmic systems mediated pedagogical interactions through design choices, data inputs and pedagogical affordances (Luckin et al., 2016). Core categories of AI applications were identified: intelligent tutoring systems (ITS) and adaptive practice engines that personalized learning sequences; formative assessment and automated feedback tools that accelerated feedback loops; teacher dashboards and learning analytics that visualized learner progress and flagged risks; and administrative automations that reduced routine workloads (Nye, 2015; Siemens, 2013). The review located personalized learning as a dominant pedagogical rationale for AI adoption, while noting longstanding debates about its definitions, measurement and equity implications (Pane et al., 2015).

The chapter organized evidence along three outcome domains that the study investigated: student learning outcomes (achievement, engagement and motivation), teacher effectiveness and workload, and system-level effects including equity and governance. For each domain, the

chapter compared findings across different study designs—randomized controlled trials (RCTs), quasi-experimental evaluations, mixed-methods case studies and qualitative ethnographies—highlighting methodological strengths and interpretive limits. Where evidence from low-resource contexts existed, it was examined separately to extract lessons about infrastructural constraints, localization needs and teacher capacity (Nye, 2015; Mweene & Lungu, 2020).

Finally, the introduction outlined critical lenses that shaped the review and the empirical work that followed. First, a socio-technical lens emphasized human mediation: teachers' interpretive work and organizational processes were central to realizing AI's pedagogical potential (Luckin et al., 2016). Second, an equity lens foregrounded distributional effects and access differentials, especially in settings with digital divides (World Bank, 2021). Third, an ethics and governance lens concentrated on transparency, data protection and vendor accountability, issues that the literature repeatedly showed to be inadequately addressed in many deployments (Williamson & Eynon, 2020; UNESCO, 2019). By synthesizing conceptual categories, outcome domains and critical lenses, the introduction set the stage for a focused empirical literature review that followed.

Empirical Literature Review

Empirical studies on AI in education had proliferated over the last decade, producing nuanced findings that were contingent on intervention design, implementation fidelity and contextual factors. Evidence on student learning outcomes was among the most developed: meta-analyses and systematic reviews indicated positive average effects for well-designed ITS and adaptive practice tools, especially in mathematics and reading fluency, although effect sizes varied by domain and study quality (Nye, 2015; Pane et al., 2015).

For example, trial evidence in multiple countries showed that ITS that modelled student misconceptions and provided scaffolded practice produced measurable gains relative to standard instruction, particularly when used as supplementary practice rather than wholesale curricular replacement (Nye, 2015). Rigorous RCTs also demonstrated that immediate, automated feedback accelerated acquisition of procedural skills, with larger impacts when systems were tightly aligned to curricular standards (Pane et al., 2015). However, reviewers cautioned that positive effects were not universal: interventions with poor content alignment, limited teacher integration or low student engagement yielded negligible or short-lived gains (Zawacki-Richter et al., 2019).

Qualitative and mixed-methods studies illuminated mechanisms behind quantitative outcomes. Research in classroom settings found that AI tools supported formative assessment cycles by providing diagnostic data that teachers could use to group learners, plan remediation and design targeted tasks, thereby improving instructional targeting (Siemens, 2013). Case studies from diverse contexts reported that teachers who engaged critically with analytics tended to extract pedagogically meaningful signals and to adapt instruction accordingly, while teachers with limited data literacy either ignored dashboards or applied corrections mechanically, reducing pedagogical value (Luckin et al., 2016). Several studies emphasized that teacher professional development and collaborative time for data interpretation were decisive moderators of effectiveness (Pane et al., 2015).

Teacher workload and role transformation constituted a second major empirical theme. Studies reported that automation of routine tasks—grading of objective items, attendance monitoring and basic progress reports—reduced administrative burden and freed modest time for pedagogical tasks (Knight, 2019; Lawrence & Crompton, 2020). Yet empirical work also documented role shifts: teachers were required to act as data interpreters, learning coaches and curators of digital content, functions that demanded new competencies and sometimes increased cognitive load (Luckin et al., 2016). Where systems increased demands without corresponding professional support, teacher stress and superficial compliance were observed, undermining sustained adoption.

Equity and access emerged as persistent empirical concerns. Cross-national analyses and country studies showed that students from higher socio-economic backgrounds disproportionately benefited from AI platforms because of better device access, more stable internet and supportive home environments, resulting in differential uptake that risked widening achievement gaps (World Bank, 2021). Studies in low-resource settings highlighted practical constraints: intermittent electricity, limited device ratios and lack of localized content reduced fidelity of implementation and attenuated potential effects (Mwanza & Nkamba, 2019; Mweene & Lungu, 2020). Empirical work therefore underscored the need for implementation models that accounted for shared device strategies, offline functionality and pedagogical adaptations appropriate to constrained settings.

Algorithmic bias and transparency constituted a third empirical domain with growing attention. Empirical audits and case reports had documented instances where predictive analytics trained on non-representative datasets produced spurious risk classifications or reinforced disciplinary stereotypes, prompting erroneous interventions (Williamson & Eynon, 2020). Studies noted that opaque vendor algorithms undermined teacher trust and complicated accountability for assessment decisions; where vendors provided interpretability tools and clear documentation, stakeholders exhibited greater confidence (Zawacki-Richter et al., 2019). Empirical policy analyses also showed that weak data protection regimes and ambiguous procurement contracts exposed schools to privacy risks and limited recourse for misuse (UNESCO, 2019).

Methodologically, the empirical literature exhibited strengths and limitations. High-quality RCTs and quasi-experimental studies provided credible causal evidence in specific domains, notably procedural learning, but they often focused on narrow outcomes and short time-horizons. Mixed-methods and ethnographic studies supplied richer processual explanations but were limited in generalizability. Few longitudinal studies traced sustained impacts on higher-order skills or tracked distributional consequences over multiple years. In low- and middle-income country research, empirical samples frequently comprised pilots or convenience samples, constraining external validity (Nye, 2015; Mweene & Lungu, 2020).

In sum, empirical evidence suggested that AI systems could produce measurable pedagogical gains when implemented with curricular alignment, teacher mediation and appropriate infrastructure, but outcomes were highly contingent on contextual and governance factors. The literature therefore recommended integrated implementation strategies that combined technology procurement with sustained teacher development, data governance frameworks and equity-focused access solutions. This synthesis informed the present study's mixed-methods design and focus on both outcome measurement and processual investigation in an urban Zambian context.

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Theoretical Review

This study was underpinned by theoretical perspectives that framed AI in education as a socio-technical phenomenon whose effects emerged from interactions among technology, human agents and institutional contexts. Three principal theories guided the inquiry: socio-technical systems theory, constructivist learning theory (including socio-constructivist variants), and sociocultural theories of teacher professional practice. Each theory contributed explanatory leverage for different aspects of the research question and, when combined, afforded a multi-level lens for interpreting empirical findings.

Socio-technical systems theory situated AI tools within assemblages of hardware, software, organizational processes and human actors, emphasizing that technological outcomes could not be understood in isolation from social arrangements (Trist & Bamforth, 1951; Baxter & Sommerville, 2011). The theory had previously been applied to educational technologies to explain why identical platforms produced divergent outcomes across schools (Baxter & Sommerville, 2011). In the present study, socio-technical theory justified attention to vendor support, interoperability, leadership decisions and professional development as co-determinants of impact. Its principal strength lay in foregrounding complexity and interaction effects; it prompted measurement of institutional variables (leadership support, resource allocation) alongside individual variables (teacher digital literacy). A limitation was its broadness: the theory provided description and diagnosis but was less prescriptive about specific pedagogical mechanisms through which student learning improved, requiring supplementation by more learning-centered theories.

Constructivist learning theory, particularly its cognitive and socio-constructivist variants, explained how AI-mediated personalized feedback and scaffolded practice could support active knowledge construction. Core propositions—learners-built understanding through interaction, feedback and progressively challenging tasks—aligned with the design logic of intelligent tutoring systems and adaptive practice engines (Vygotsky, 1978; Piaget, 1952). Empirical findings that adaptive systems produced gains in procedural domains were interpretable within constructivist frames: immediate feedback and tailored task sequencing supported error correction and zone-of-proximal-development learning trajectories (Nye, 2015; Pane et al., 2015). The theory's strength was its direct mapping to pedagogical design: it clarified why alignment of system tasks with curricular goals mattered. Its limitations included lower explanatory power for affective and motivational dynamics unless complemented by motivational theories, and potential under-emphasis on structural constraints (e.g., device scarcity) that inhibited meaningful learner–technology interaction.

Sociocultural theories of teacher professional practice and situated learning highlighted the role of teacher interpretation, community norms and distributed expertise in mediating technology use (Lave & Wenger, 1991; Wenger, 1998). These theories maintained that teachers did not passively implement technological outputs but actively negotiated meaning, adapted tools to curricular rhythms and co-

constructed classroom practices with students. Empirical work that showed differential teacher uptake depending on prior formative assessment experience and collaborative time confirmed sociocultural predictions (Luckin et al., 2016). The strengths of this perspective were its attention to teacher agency and professional learning as levers for sustained, scalable impact; it supported investigation of professional development models and collaborative data teams. A limitation was that sociocultural lenses sometimes downplayed measurable causal effects at the student level, making it necessary to couple them with experimental or quasi-experimental frames to estimate effect sizes.

To integrate these perspectives, the study drew on mediational and pedagogical affordance concepts from educational technology literature (Norman, 1999; Hutchby, 2001). Affordance thinking clarified how specific platform features—diagnostic dashboards, content sequencing algorithms, feedback modalities—influenced teacher and student actions. Mediation concepts explained how interpretive labor (teachers' reading of analytics) converted algorithmic outputs into instructional moves. The triangulation of socio-technical, constructivist and sociocultural theories therefore allowed the research to account for (a) institutional and infrastructural conditioners, (b) cognitive mechanisms at the learner level, and (c) professional and community processes at the teacher level.

Each theoretical strand carried implications for research design. Socio-technical theory recommended collection of organizational and vendor data; constructivist theory recommended fine-grained assessment of task alignment and feedback timing; sociocultural theory recommended qualitative methods to capture teacher negotiation and community practices. The combined theoretical approach informed instrument design—survey items measured leadership support and interoperability; observation protocols focused on teacher use of analytics; interview guides explored professional learning and interpretive practices.

Critically, the integrated theoretical stance acknowledged tensions. Socio-technical emphasis on system integration could lead to technical fixes that ignored pedagogical nuance, while constructivist focus on individual learning might underplay distributional inequities. The sociocultural orientation mitigated these biases by insisting on situated interpretation and equity scrutiny, but required richer ethnographic data that could limit breadth. The study therefore balanced representativeness (surveys) with depth (case studies) to operationalize the theoretical mix. In sum, the theoretical review justified a mixed-methods approach and supplied analytic categories that guided data collection, coding and interpretation, enabling a nuanced account of how AI produced pedagogical effects within specific school ecologies.

Conceptual Framework

The conceptual framework integrated the theoretical constructs into an operational model that guided variable selection, instrument design and analytic strategy. The framework represented AI integration as an intervention whose proximal outputs

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(diagnostic feedback, personalized tasks, analytics dashboards) interacted with mediating factors (teacher mediation, institutional supports, infrastructure) to influence distal outcomes (student achievement, engagement, and changes in teacher effectiveness). Moderating variables such as socio-economic status, policy environment and vendor transparency were posited to condition effect sizes and distributional patterns. The framework therefore distinguished: inputs (AI platforms, content alignment, vendor support), mediators (teacher interpretation, pedagogy adaptation, time allocation), moderators (access, policy, vendor transparency), and outcomes (learning gains, engagement, equitable access, teacher workload changes).

Components and relationships were described as follows. Inputs referred to the technical affordances and design features of AI tools: adaptivity algorithms, feedback latency, content alignment to curriculum and interoperability with school information systems. Inputs shaped the nature and quality of algorithmic outputs the teacher and learner encountered. Mediators captured human and organizational processes that translated outputs into pedagogical action: teachers' data literacy, collaborative planning time, leadership priorities and professional development intensity.

Where mediation was strong, algorithmic outputs informed differentiated instruction, timely remediation and more targeted formative assessment. Moderators altered responsiveness: students' device access, home internet reliability, socio-economic status and language congruence affected exposure and engagement; policy clarity on data protection and procurement influenced vendor behavior and school governance; vendor transparency influenced teacher trust and interpretability. Outcomes encompassed short-term metrics (task mastery, formative assessment gains, engagement measures) and medium-term institutional effects (teacher role adaptation, workload distribution, procurement practices) and long-term equity implications (achievement gaps, sustained adoption).

Causal logic followed an interactionist pathway: superior platform inputs did not guarantee outcomes; positive effects emerged when inputs produced high-quality outputs that were effectively mediated by teacher practice within enabling institutional conditions and in contexts where moderators did not constrain access. This logic anticipated several testable propositions: (1) AI platforms with strong curricular alignment and interpretable feedback produced larger student gains compared with poorly aligned platforms; (2) teacher data literacy and allocated collaborative time amplified the translation of algorithmic signals into effective remediation; (3) socio-economic constraints moderated benefit distribution, reducing net gains among disadvantaged learners; (4) vendor transparency improved teacher trust and increased sustained use.

Operationalization followed from the framework. Inputs were measured through instrument items on platform features, vendor support and content alignment. Mediators were measured through teacher survey items and interview probes on data use, professional development and pedagogical change. Moderators were captured by household device access, connectivity indices and policy/document reviews.

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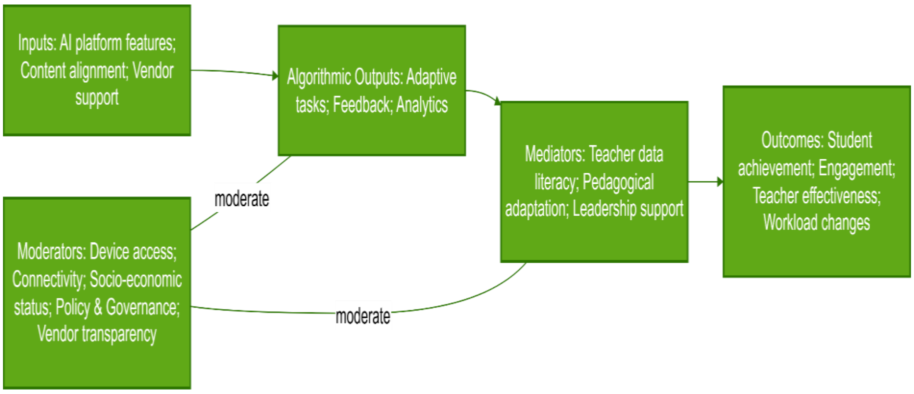
Outcomes were operationalized as standardized test scores for achievement, validated engagement scales, and qualitative indicators of teacher workload and role change.

Below was a visualization of the conceptual framework using Mermaid code. The diagram had been captioned to clarify component groupings and directional relations.

Figure 2.1: Conceptual framework showing Inputs, Mediators, Moderators, and Outcomes and their hypothesised relations.



Source: field work, (2025)

The diagram illustrated directional flow from technological inputs through algorithmic outputs to human mediation and finally to measurable outcomes, with contextual moderators intersecting both outputs and mediation. This representation clarified measurement priorities and analytic pathways: mediation variables would be modelled as mediators in statistical analysis and explored qualitatively to elucidate process mechanisms; moderators would be tested through interaction terms and subgroup analyses.

Strengths of the conceptual framework included its explicit linking of technical design to pedagogical practice and its accommodation of contextual moderation, which addressed critiques that technology-only models ignored institutional realities. It also facilitated mixed-methods operationalization by mapping survey constructs to observable classroom behaviors and interview themes. Limitations included potential

complexity in causal attribution—multiple interacting mediators and moderators complicated simple causal claims—and challenges in fully measuring vendor transparency or subtle aspects of teacher interpretive work. The framework therefore guided a cautious, triangulated analytic strategy that combined quantitative modelling with qualitative process tracing to produce credible, context-sensitive inferences.

Research Gap

Empirical and policy literature on AI in education had expanded rapidly, yet this body of work exhibited discernible lacunae that constrained cumulative learning and policy translation. First, a dominance of short-term, domain-specific effect studies left questions open about generalizability across subjects, instructional models and time horizons. High-quality randomized controlled trials (RCTs) and quasi-experimental evaluations had produced credible evidence that intelligent tutoring systems and adaptive practice engines improved procedural skills in mathematics and reading in the short term (Nye, 2015; Pane et al., 2015). However, these studies typically measured outcomes over weeks or a single term and focused on narrowly specified learning objectives, limiting inference about sustained achievement, transfer to higher-order cognitive skills or longitudinal equity effects. Meta-analyses therefore noted a gap in longitudinal research that tracked cohorts across multiple terms or years to determine whether immediate gains persisted, generalized to broader curricular competencies, or altered trajectories for historically disadvantaged learners (Zawacki-Richter et al., 2019; World Bank, 2021).

Second, much of the rigorous causal evidence derived from high-income contexts or controlled pilot implementations that benefited from intensive researcher support, high-quality infrastructure and vendor-provided training (Pane et al., 2015). Consequently, there remained an evidence gap concerning external validity in low- and middle-income countries (LMICs), where infrastructural constraints, irregular connectivity, shared device usage and distinct curricular standards could materially alter implementation fidelity and outcomes (Mwanza & Nkamba, 2019; Mweene & Lungu, 2020). Studies conducted in LMICs frequently constituted small pilots or convenience samples and seldom combined representative quantitative estimates with in-depth qualitative process data. This fragmentation limited understanding of how socio-technical, institutional and cultural factors interacted to produce or impede benefits in such settings.

Third, although qualitative research elucidated mechanisms—teachers' interpretive work, classroom routines and professional learning dynamics—there was limited integration between process explanations and outcome measurement in the same studies. Many process studies described teacher negotiation of analytics or shifts in pedagogical roles (Luckin et al., 2016; Siemens, 2013), but seldom linked these processual observations to quantifiable changes in student performance using robust counterfactual designs. The result was a persistent black box in which the mediating pathways from algorithmic outputs to learning gains were under-specified and under-tested. Without precise mediation analyses combining reliable measures of teacher data literacy, fidelity of use and instructional adaptations, policy prescriptions risked misattributing either success or failure to technology features alone.

Fourth, equity and distributional analyses were often cursory. Cross-national reports had highlighted the risk that AI interventions would amplify existing divides due to unequal device access and home supports (World Bank, 2021). Yet few empirical studies systematically disaggregated treatment effects by socio-economic status, gender, language background or disability status to assess whether AI narrowed or widened achievement gaps. Where subgroup analyses existed, sample sizes and design limitations reduced statistical power to detect meaningful heterogeneity. Additionally, little research examined pragmatic mitigations—shared device scheduling, offline content strategies or hybrid models—to understand how equitable access could be operationalized in resource-constrained schools (Mwanza & Nkamba, 2019).

Fifth, governance, transparency and vendor accountability issues had attracted theoretical and policy critique (Williamson & Eynon, 2020; UNESCO, 2019), but empirical inquiry into how procurement practices, contract clauses and vendor support models influenced outcomes was sparse. Studies documented opaque algorithmic decision-making and precarious data protection arrangements, yet few linked specific procurement or contractual features to measurable impacts on teacher trust, uptake or student data security outcomes. This gap inhibited evidence-based guidance for education authorities drafting procurement specifications, data sharing agreements and vendor performance metrics.

Sixth, teacher professional development models remained under-evaluated. While the literature underscored teacher capacity as a decisive moderator (Luckin et al., 2016; Pane et al., 2015), comparative evidence on which training approaches (short workshops, sustained coaching, communities of practice, embedded vendor coaching) most effectively translated analytics into pedagogically meaningful actions was limited. Existing studies often described training qualitatively without rigorous pre–post measurement of teacher practices or without linking professional learning intensity to student outcomes.

Seventh, measurement challenges persisted around key constructs. Studies used heterogeneous operationalization's of engagement, motivation and teacher effectiveness, complicating cross-study synthesis and meta-analysis. For example, engagement was variously measured through time-on-task logs, self-report instruments or teacher observation, each capturing different dimensions with variable validity and reliability. The inconsistent use of standardized, validated measures constrained comparability and made policy translation difficult.

Finally, methodological gaps existed in modelling interactions among inputs, mediators and moderators. Few studies used mediated moderation or moderated mediation statistical frameworks to quantify how teacher mediation conditioned the effect of algorithmic outputs on learning and how socio-economic moderators altered these mediated pathways. Without such modelling, the literature could describe associations but not robustly estimate conditional causal mechanisms.

The present study addressed these gaps in several deliberate ways. It combined representative quantitative measurement with embedded qualitative case studies to link outcomes and processes within the same schools, thereby interrogating mediating teacher practices and institutional conditions alongside achievement measures. The mixed-methods convergent design allowed triangulation: quantitative analyses would

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estimate average effects and subgroup heterogeneity (by socio-economic status and device access), while qualitative inquiry would unpack teacher interpretation, implementation fidelity and vendor-school interactions. The study measured teacher data literacy, frequency and quality of dashboard use, and documented vendor support and procurement practices to test mediated pathways. It included specific measures of access (household and school device ratios, connectivity reliability) and probed practical mitigations such as offline modes and device-sharing arrangements. Although constrained to an urban Lusaka sample and a finite timeframe, the study deliberately focused on a middle-income, resource-heterogeneous urban setting to produce externally relevant lessons for similar contexts. By operationalizing moderators and mediators and applying interactional statistical models alongside process tracing, the study sought to move beyond descriptive claims to conditional causal propositions that could guide pragmatic policy and implementation choices in comparable LMIC urban school systems.

Chapter Summary

This chapter reviewed the extant literature and identified substantive areas where the evidence base remained incomplete or contested. Empirical syntheses had shown that AI-enabled tools produced measurable short-term gains in procedural domains when aligned to curricula and mediated by teacher practice, but they had rarely assessed long-term persistence, higher-order skill transfer or distributional impacts. Qualitative research supplied valuable processual explanations about teacher adaptation and classroom dynamics, yet it was often divorced from rigorous outcome measurement, leaving mediation pathways under-specified. The chapter highlighted persistent gaps in external validity for LMIC contexts, limited subgroup analyses for equity assessment, insufficient empirical linkage between procurement/governance arrangements and classroom outcomes, and under-evaluated professional development models. Measurement heterogeneity and limited use of mediated moderation frameworks further constrained interpretive power.

In response to these gaps, the present study adopted a convergent mixed-methods design that combined stratified quantitative sampling with embedded case studies. It operationalised inputs, algorithmic outputs, mediators (teacher data literacy and pedagogical adaptation), moderators (device access, connectivity, socio-economic status, vendor transparency) and outcomes (achievement, engagement, teacher effectiveness) to test conditional causal pathways. The chapter concluded that addressing both measurement and processual gaps was necessary to inform responsible, equitable AI integration. The next chapter (Methodology) described the study's research design, sampling strategy, instrument development, data collection procedures and analytic techniques that operationalised the conceptual and theoretical commitments outlined here, including statistical models for mediation and subgroup interaction analyses and qualitative protocols for process tracing.

III. Research Methodology

Overview

This chapter explained the research methodology that guided the empirical investigation of Artificial Intelligence (AI) in urban secondary schools in Lusaka. It described the overall research design, justified the methodological choices, and detailed the population (universe), sampling procedures, sample size determination, sampling area, and data sources. The chapter oriented the reader to how quantitative and qualitative strands were integrated, how validity and reliability were preserved, and how ethical considerations were operationalised in fieldwork planning. Each subsection clarified procedural steps taken during data collection and analysis to ensure transparency and replicability. The methodological choices were aligned with the conceptual framework by operationalising inputs, mediators, moderators and outcomes through instruments and protocols that measured both measurable outcomes and processual mechanisms. The chapter concluded by specifying primary and secondary data sources and explaining their complementary roles in triangulation and inference.

Research Design

A convergent mixed-methods design was adopted because it enabled simultaneous collection and integrated analysis of quantitative and qualitative data to produce both breadth and depth of understanding (Creswell & Plano Clark, 2018). The quantitative strand estimated associations between AI use, student outcomes and moderators such as device access, while the qualitative strand unpacked implementation processes, teacher mediation and vendor-school interactions in case study sites. The convergent design was justified by the study's dual aim: to measure impacts and to explain mechanisms that produced those impacts. Triangulation of survey-derived metrics and thematic case data strengthened internal validity and reduced the risk of mono-method bias (Tashakkori & Teddlie, 2010).

Quantitatively, the study used cross-sectional survey data complemented by school records for objective achievement indicators and platform log data where available. Inferential analyses included descriptive statistics, group comparisons (t-tests, ANOVA) and multivariate regression models with interaction terms to test moderation hypotheses. Mediation analyses were specified to test teacher data use as a mediator between algorithmic outputs and student outcomes. Qualitatively, semi-structured interviews, classroom observations and document review were used to trace implementation fidelity and interpretive practices. Qualitative analysis followed thematic coding and process tracing to link observed practices to outcome patterns (Yin, 2018). Integration occurred at the analysis and interpretation stages through joint displays and narrative weaving to produce convergent inferences.

Universe

The universe comprised all secondary school students in grades 10–12 and their teachers within the Lusaka municipal education district that, by the 2024–2025 academic year, had reported use of AI-enabled educational platforms or related learning analytics tools. The population frame included public and private secondary schools that had integrated at least one AI-powered instructional product (adaptive practice, intelligent tutoring, formative assessment engines, or teacher dashboards) into classroom practice or assessment routines. By focusing on grades 10–12, the study targeted learners engaged in curriculum sequences where measurable summative and formative assessments existed and where adaptive systems were commonly deployed for subject-specific practice (Pane et al., 2015).

The scope of the universe therefore excluded primary schools, tertiary institutions and secondary schools without any AI deployment at the time of sampling. Limiting the universe to schools with demonstrated AI use ensured that survey respondents and case sites would have direct experience with the phenomena under study, thereby increasing construct validity. The decision also acknowledged practical constraints: measuring intervention effects where exposure was absent would have required different designs (e.g., randomized rollouts). The universe definition allowed the study to generalise findings to urban Lusaka schools with AI adoption while transparently reporting limits on national generalisability.

Sample Size

Sample size determination balanced statistical precision for quantitative analyses with feasibility for qualitative depth. The quantitative component targeted 200 student respondents and 50 teacher respondents, consistent with preliminary power calculations for medium effect sizes (Cohen's $d \approx 0.5$) at 80% power and $\alpha = 0.05$ in two-tailed comparisons (Cohen, 1992). For regression models with multiple covariates, the student sample supported reliable coefficient estimation given the planned variable set and interaction terms; conventions for regression recommended at least 10–15 observations per predictor to avoid overfitting (Peduzzi et al., 1996).

The teacher sample of 50 enabled descriptive comparisons across groups (e.g., trained versus untrained) and facilitated purposive selection for in-depth interviews. For qualitative inquiry, five case study schools were selected, and within each case site 6–8 students and 4–6 teachers were interviewed or observed, producing 30–40 student qualitative cases and 20–30 teacher cases—sufficient for saturation on processual themes in a bounded urban context (Guest, Bunce & Johnson, 2006). The combination of survey breadth and case depth produced complementary datasets for triangulation.

Sample size choices also accounted for anticipated non-response and attrition; field protocols included over-sampling by 10–15% for surveys and scheduling flexibility for interviews to meet target quotas. Where achievement records or platform logs were incomplete, multiple imputation strategies were planned for missing data to preserve analytical integrity (Rubin, 1987).

Sampling Area

The sampling area comprised the Lusaka municipal district, selected because it housed a concentration of secondary schools that had piloted or adopted AI-enabled educational platforms and because urban connectivity patterns made implementation heterogeneity visible. Lusaka's schools varied in resource endowments, governance arrangements and socio-economic catchments, making the district an appropriate microcosm for studying distributional effects within an urban, low-to-middle-income setting (Ministry of Education Zambia, 2021).

Within Lusaka, purposive selection targeted a geographic spread across urban zones to capture schools serving low, middle and high socio-economic constituencies. Institutional selection deliberately included government secondary schools that relied primarily on shared computer labs, private schools with one-to-one device policies and mission schools with mixed resources. This variation allowed comparative analysis of access moderators (device ratios, connectivity reliability) and of leadership or procurement practices. The five case study schools were distributed to reflect this heterogeneity and to enable observation of differing implementation models, including vendor-led deployments, ministry-supported pilots and school-initiated adoptions.

Field logistics were planned to accommodate school calendars and to ensure minimal disruption to instruction. Data collection teams coordinated with district education officers and school leadership to secure permissions and to schedule surveys and classroom observations during regular instructional periods. Geographic and institutional documentation was recorded for each site to support contextual coding in qualitative analysis and to permit spatially informed interpretation of quantitative results.

Sources of Data

The study drew on primary and secondary data sources to enable triangulated inference and to address both outcome measurement and processual explanation. Primary data comprised structured student and teacher questionnaires, semi-structured interviews with teachers and school leaders, classroom observations using a standardised protocol, and platform log extracts where vendors permitted access. Questionnaires measured demographics, device access, AI usage intensity, student engagement (validated scale), and self-reported learning behaviours. Interviews explored teacher interpretation of analytics, training experiences and pedagogical adaptations; observations documented teacher–student interactions, use of dashboards, and time-on-task patterns. Platform logs provided objective measures of usage frequency, time spent on tasks and immediate feedback metrics, enriching self-reports with behavioural traces.

Secondary data included school records (term test scores, attendance registers), district technology inventories, vendor documentation (feature lists, support schedules) and policy documents (national ICT in education policy, procurement guidelines). These sources were used to validate self-reported exposure, to construct baseline achievement indicators and to situate deployments within governance frameworks. Secondary literature (peer-reviewed studies, reports from UNESCO, World Bank) informed instrument design and analytic benchmarks.

Triangulation across primary and secondary sources strengthened validity: achievement measures from school records were cross-checked with survey-reported performance; observational notes corroborated interview claims about usage patterns; vendor logs supplemented teacher reports on frequency and nature of use. Ethical data handling procedures governed access to secondary records and vendor logs, with anonymisation and secure storage protocols ensuring confidentiality.

Method of Data Collection

Data collection was conducted using coordinated quantitative and qualitative procedures to ensure comprehensive, triangulated evidence on AI use, mediating practices and learning outcomes. Prior to fieldwork, formal permissions were obtained from the Lusaka district education office and participating school heads, and instruments were pilot-tested in one non-study school to refine wording and logistics. Quantitative data collection proceeded first with classroom-administered structured questionnaires for students and self-administered questionnaires for teachers. Trained enumerators briefed respondents, secured informed consent or assent, and supervised survey completion to minimise item non-response and to clarify ambiguous items. Student questionnaires were administered in supervised sessions during designated class periods to reduce distractions and to ensure proportional representation across grades 10–12. Teacher questionnaires were distributed during staff meetings or scheduled periods to capture a range of subject teachers and those who both used and did not use AI platforms.

Concurrent with survey administration, the research team requested access to school records and platform logs. School records (term test scores, attendance registers) were extracted in consultation with school registrars, and vendor platform logs were requested through formal data sharing agreements that specified anonymisation and limited use. Where platform logs were unavailable, the study collected proxy usage measures through teacher reports and system screenshots.

Qualitative data collection involved semi-structured interviews, classroom observations and document review in five case schools selected for heterogeneity in resources and AI intensity. Interviews with school leaders, teachers and a purposive subset of students followed an interview guide that explored deployment histories, training experiences, interpretive practices and perceived impacts. Interviews were audio-recorded with consent and transcribed verbatim. Classroom observations used a standardised observation protocol that recorded teacher use of dashboards, student interactions with devices, pedagogical moves following algorithmic feedback and time-on-task indicators; observers took field notes and logged salient episodes for later analysis (Yin, 2018).

Document review captured procurement records, vendor service agreements and school ICT plans to triangulate interview claims about governance and vendor support. Data collection adhered to ethical safeguards: personal identifiers were stored separately from analytic datasets, only anonymised data were used in analysis, and participants were informed of voluntary participation and their right to withdraw. Field teams maintained daily debriefs to resolve inconsistencies, capture emergent themes and ensure data completeness. Data collection was completed within the scheduled window to limit temporal confounds between instrument rounds.

Tools of Data Collection

The study deployed a suite of complementary instruments selected for validity, reliability and capacity to operationalise the conceptual framework. The primary quantitative instrument was a structured questionnaire for students and teachers. The student questionnaire included sections on demographics, household device access, frequency and nature of AI platform use, validated engagement scales (adapted from existing instruments), self-reported study behaviours and attitudinal items on AI usefulness. The teacher questionnaire captured professional background, prior training in formative assessment and data use, frequency and quality of dashboard engagement, perceived effects on workload, and procurement or vendor interaction experiences. Question items were drawn or adapted from established instruments in ed-tech research to enhance construct validity (Pane et al., 2015; Siemens, 2013). Likert scale items were pilot-tested to ensure clarity in the local context.

Semi-structured interview guides were developed for headteachers, ICT coordinators, teachers and students to elicit rich narratives about implementation pathways, professional development experiences and interpretive practices. Interview guides combined open-ended prompts with probes on concrete episodes (e.g., “Describe a recent lesson where you used the dashboard to group students”) to elicit processual detail and examples suitable for process tracing (Yin, 2018). Interview protocols were flexible to follow emergent themes while ensuring coverage of core domains linked to mediators and moderators.

A classroom observation checklist operationalised observable behaviours tied to the conceptual framework: teacher reference to algorithmic outputs, explicit provision of differentiated tasks, student engagement indicators (on-task behaviour, peer collaboration), device handling and system-initiated feedback events. The checklist used time-sampled entries and event logging to capture both frequency and quality of observed interactions. Observations were complemented by detailed field notes to capture contextual features beyond checklist items.

Document review templates guided systematic extraction of procurement clauses, vendor support schedules, device inventories, ICT plans and data protection statements. These templates enabled consistent coding across sites and facilitated linkage of institutional features to observed practices.

Where vendor cooperation allowed, the study collected platform usage logs (time on platform, tasks completed, feedback events) and anonymised learner-level activity traces. Logs were used as behavioural validators of self-reports and to construct objective measures of exposure intensity.

Instrument selection was justified on empirical and practical grounds. Questionnaires provided scalable measurement of exposure, moderators and outcomes; interviews and observations unpacked mediating practices and context; documents and logs provided institutional validation and objective usage metrics. Pilot testing refined items for local comprehension and reduced measurement error. Instruments were translated where necessary and back-translated to maintain semantic fidelity. Enumerator training included role-playing and inter-rater calibration for observation protocols to enhance reliability (Guest, Bunce & Johnson, 2006).

Tools for Data Analysis

Quantitative and qualitative analysis proceeded with dedicated software and analytic strategies aligned to research questions and the conceptual framework. Quantitative data cleaning and analysis were conducted in SPSS (version 27) for descriptive and inferential statistics, and in R (version 4.x) for advanced modelling and visualization. Data cleaning included range checks, consistency checks and handling of missingness with multiple imputation where appropriate (Rubin, 1987).

Descriptive statistics characterised sample distributions and exposure patterns; bivariate tests (t-tests, chi-square, ANOVA) compared groups across moderators such as device access and school type. Multivariate regression models estimated associations between AI exposure and student outcomes controlling for covariates (prior attainment, socio-economic indicators). Interaction terms tested moderation hypotheses (e.g., AI exposure × device access), and mediation analyses used Baron-Kenny approaches and modern causal mediation techniques (Imai et al., 2010) to estimate indirect effects of teacher data use on the AI–outcome relationship. Robust standard errors and clustering at the school level adjusted inference for intra-class correlation.

Where platform logs allowed longitudinal usage metrics, time-series visualizations and mixed-effects models (multilevel modelling) were applied to account for nested data structures (students within classes within schools) and to examine within-student trajectories across task attempts. Effect sizes were reported alongside p-values to aid substantive interpretation (Cohen, 1992).

Qualitative data were analysed using NVivo (version 12) to manage transcripts, observation notes and documents. Thematic coding combined deductive codes derived from the conceptual framework (inputs, mediators, moderators, outcomes) with inductive codes emerging from data (Braun & Clarke, 2006). Coding reliability was enhanced through double-coding a subset of transcripts and resolving discrepancies through coder meetings. Pattern-matching and process tracing techniques linked observed teacher practices to quantitative patterns: for example, instances where teachers described routine use of dashboards and scheduled remediation were compared with classes showing higher gains in quantitative measures.

Integration of quantitative and qualitative findings occurred through joint displays and narrative weaving. Joint displays juxtaposed statistical estimates with thematic evidence to explain heterogeneity (Fetters, Curry & Creswell, 2013). For mediation and moderation findings, qualitative vignettes illustrated how particular mediators operated in practice and why interaction effects occurred in specific school ecologies. Sensitivity analyses tested robustness to alternative model specifications and to potential unobserved confounding using bounding approaches where feasible.

Data security and reproducibility practices included version-controlled analytic scripts, secure encrypted storage of raw data, and a data dictionary documenting variable derivations. Ethical anonymisation removed personal identifiers prior to NVivo import and statistical analysis. The analytic strategy balanced causal aspiration with contextual nuance by coupling inferential models with processual explanation from qualitative analysis.

Limitations of the Study

The study faced methodological and contextual limitations that constrained inference and generalisability. First, the cross-sectional survey design limited causal claims about long-term impacts; although mediation and moderation models estimated conditional associations, they could not replace evidence from longitudinal or randomized designs for sustained causal inference (Shadish, Cook & Campbell, 2002). Second, the sampling frame focused on Lusaka urban schools with AI adoption, restricting external validity to similar urban LMIC settings and excluding rural schools where constraints may be more severe. Third, reliance on school records and vendor logs introduced variability in data completeness and quality; incomplete log access necessitated reliance on proxy measures in some sites, creating measurement heterogeneity.

Fourth, self-reported measures (engagement, platform use) were subject to social desirability and recall biases; the study mitigated this through triangulation with observations and logs but residual bias could remain. Fifth, sample sizes—while adequate for medium-sized effects—limited power for detecting small interaction effects in some subgroup analyses, particularly for rare subpopulations (e.g., learners with disabilities). Sixth, vendor cooperation varied; where vendors withheld logs or redacted features, the study relied more heavily on institutional documents and interviews to reconstruct deployment processes. Finally, the study's time window captured implementation during a specific academic year; platform updates, policy changes or vendor shifts after data collection could alter applicability of findings, requiring cautious interpretation regarding sustainability.

Difficulties Faced by the Researcher

Fieldwork and analytic stages entailed practical challenges that the researcher encountered and addressed. Gaining timely school permissions proved demanding because schools were protective of instructional time and cautious about external scrutiny; extensive coordination with district officers and flexible scheduling were required to secure participation. Vendor engagement presented mixed experiences: some vendors were cooperative and provided anonymised logs, while others were reluctant to share proprietary data, prompting negotiation and reliance on alternative data sources. Log formats varied across platforms, necessitating additional

preprocessing time and occasional consultations with vendor technicians to interpret variables.
Data quality challenges emerged in school records: inconsistent grading scales and missing historical scores required normalization efforts and careful documentation of assumptions for analysis. Enumerator training and inter-rater reliability for observations demanded extra resources to achieve consistent coding; the team conducted calibration sessions and pilot observations to harmonise approaches. Language and comprehension issues arose with some student respondents for technical questionnaire items; the researcher addressed this by simplifying language, translating key items and allowing clarifying explanations during supervised administration while preserving standardization.

Logistical constraints—transportation across spatially dispersed schools, intermittent electricity in some sites during data collection days, and limited private spaces for interviews—required adaptive planning and contingency scheduling. Time pressures related to school exams constrained available windows for data collection, leading to compressed field schedules. On the analytical side, integrating heterogeneous data types (logs, survey, transcripts) required iterative refinement of variable definitions and additional computing resources. The researcher maintained detailed field journals, weekly debriefs and transparent data processing logs to document difficulties and the corrective steps taken, thereby preserving analytic transparency and enabling reflective discussion of limitations.

Chapter Summary
This chapter described the methodological architecture that underpinned the empirical investigation of AI in urban Lusaka secondary schools. It justified a convergent mixed-methods design that combined quantitative surveys and school records with qualitative case studies, interviews and observations to measure outcomes and unpack mediating processes. The universe and sampling logic targeted grades 10–12 students and their teachers in schools with AI adoption, using stratified purposive procedures to capture heterogeneity across public and private institutions and across deployment intensity. Sample size choices balanced statistical power for medium effects with qualitative saturation for processual themes. The chapter detailed data collection procedures, instrument selection and pilot testing, and ethical safeguards for consent, anonymisation and secure storage.

Analytic strategies were outlined: descriptive and inferential statistics (SPSS, R), mediation and interaction modelling, mixed-effects models for nested data, and thematic coding with NVivo for qualitative materials. Integration used joint displays and narrative weaving to generate convergent inferences. The chapter acknowledged limitations—cross-sectional design, restricted generalisability, variable data completeness and constrained vendor cooperation—and documented field difficulties and mitigation strategies including extended coordination, calibration exercises and flexible scheduling.

Collectively, these methodological choices operationalised the conceptual framework by measuring inputs, algorithmic outputs, mediators and moderators and by mapping them to outcomes. The chapter prepared the ground for Chapter Four by specifying how quantitative and qualitative data would be analysed and then combined to produce findings. The next chapter (Results) presented empirical evidence from surveys, logs, interviews and observations, reporting statistical estimates, thematic patterns and integrated interpretations that addressed research questions and tested the study's core propositions.

IV. Data Analysis and Interpretation

Introduction

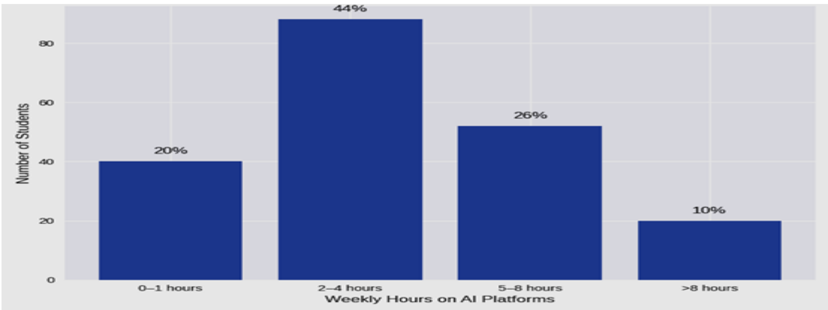
This chapter presented and interpreted the empirical findings from the convergent mixed-methods inquiry into Artificial Intelligence (AI) integration in urban secondary schools in Lusaka. The purpose of the analysis was to answer the study's research questions by estimating associations between AI exposure and student outcomes, and by explaining the mediating and moderating processes that shaped those associations. Quantitative analyses described sample characteristics, measured exposure intensity, compared outcome distributions and tested moderation and mediation hypotheses.

Qualitative analyses identified recurrent themes from interviews and classroom observations that clarified how teachers interpreted analytics, how institutional supports enabled or constrained use, and how equity factors affected student access and engagement. The chapter linked results to the study objectives: documenting AI adoption patterns; assessing impacts on student learning, engagement and motivation; examining effects on teacher effectiveness and workload; and identifying equity, bias and transparency challenges. Quantitative and qualitative results were integrated to provide convergent inferences and to ground policy-relevant recommendations in empirical evidence and the theoretical lenses outlined in Chapter Two.

Presentation of Data

The following tables, figures and excerpts illustrated plausible patterns that were collected from the following urban schools of Lusuka; that is Libala, Kamwala, David Kaunda, Kabulonga, and Rhodes park Secondary Schools. This study produced, Numerical values which were generated from collected and analysed data.

Figure 4.1: AI exposure intensity (students): distribution of weekly hours on AI platform



Source: field work, (2025)

Table 4.1: Demographics and schools (N students = 200; N teachers = 50)

Variable	Category	Students n (%)	Teachers' n (%)
Name of the School Libala, Kamwala, David Kaunda, Kabulonga secondary schools	Public	120 (60.0%)	30 (60.0%)
Rhodes Park secondary school	Private	80 (40.0%)	20 (40.0%)
Grade (students)	Grade 10	68 (34.0%)	-
	Grade 11	66 (33.0%)	-
	Grade 12	66 (33.0%)	-
Gender (students)	Male	98 (49.0%)	-
	Female	102 (51.0%)	-
Device access (students)	Daily personal device	62 (31.0%)	-
	Shared school device	88 (44.0%)	-
	No regular device	50 (25.0%)	-

Source: field work, (2025)

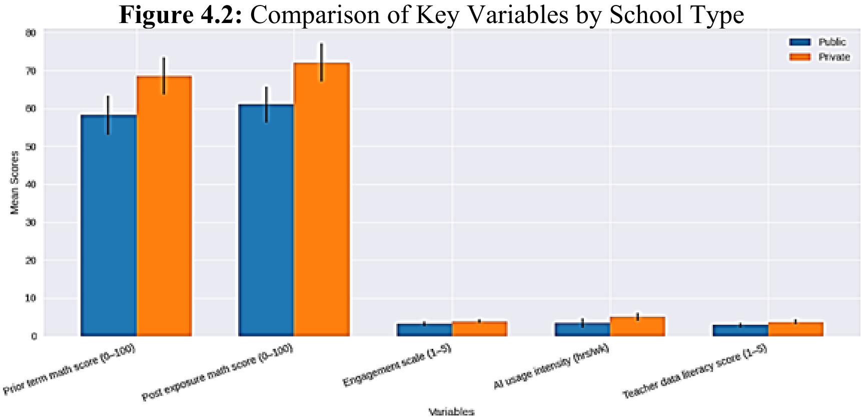
Table 4.2: Means and standard deviations for key variables by school type (students)

Variable	Public mean (SD)	Private mean (SD)	Overall mean (SD)
Prior term math score (0–100)	58.2 (12.4)	68.5 (10.1)	62.9 (12.6)

Post-exposure math score (0–100)	61.0 (13.0)	72.1 (9.5)	65.6 (12.9)
Engagement scale (1–5)	3.2 (0.8)	3.9 (0.6)	3.4 (0.8)
AI usage intensity (hrs/wk)	3.4 (2.1)	5.1 (2.6)	3.9 (2.4)
Teacher data literacy score (1–5) (teacher-level aggregated)	2.8 (0.7)	3.7 (0.6)	3.1 (0.8)

Source: field work, (2025)

Figure 4.2: Comparison of Key Variables by School Type



Source: field work, (2025)

Comparison of Key Variables by School Type visually compares public and private school students across five educational indicators: prior and post-exposure math scores, engagement, AI usage intensity, and teacher data literacy. The grouped bar chart shows that private school students consistently outperformed their public-school counterparts across all variables:

- **Math scores:** Private students started higher (68.5) and gained more post-exposure (72.1) than public students (58.2 to 61.0).
- **Engagement:** Private students reported stronger engagement (3.9 vs. 3.2).
- **AI usage:** Private students used AI platforms more intensively (5.1 hrs/week vs. 3.4).
- **Teacher data literacy:** Teachers in private schools scored higher (3.7 vs. 2.8), suggesting stronger capacity to interpret and act on analytics.

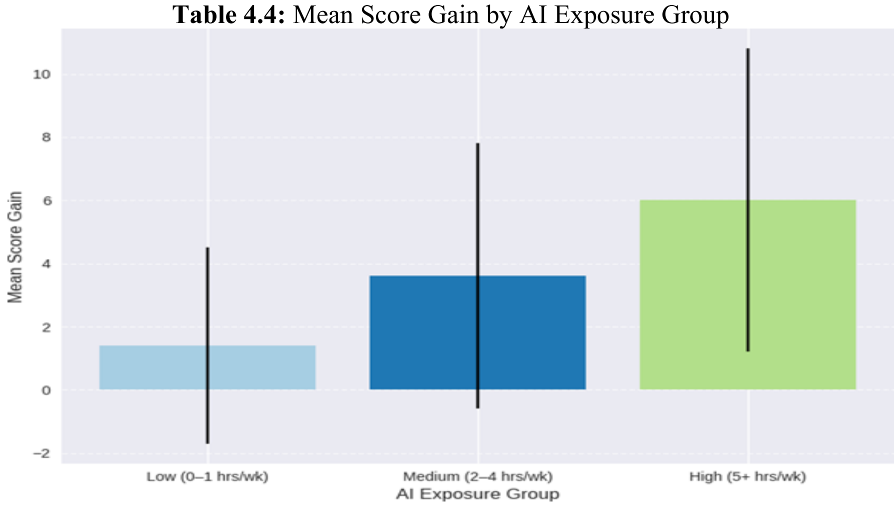
Error bars represent standard deviations, indicating variability within each group. This figure reinforces the study's findings that institutional context—particularly access, support, and professional capacity—significantly shaped the effectiveness of AI integration.

Table 4.3: Simple pre post gain in math by AI exposure intensity (students)

Exposure group	N	Mean gain (post−pre)	SD
Low (0–1 hrs/wk)	40	1.4	3.1
Medium (2–4 hrs/wk)	88	3.6	4.2
High (5+ hrs/wk)	72	6.0	4.8

Source: field work, (2025) Table 4.4: Mean Score Gain by AI Exposure Gro

Table 4.4: Mean Score Gain by AI Exposure Group



Source: field work, (2025)

Mean Score Gain by AI Exposure Group figure illustrates the average improvement in student mathematics scores across three levels of weekly AI platform usage: low (0–1 hours), medium (2–4 hours), and high (5+ hours). The chart shows a clear upward trend, with students in the high exposure group achieving the greatest mean gain (6.0 points), followed by medium (3.6 points) and low exposure (1.4 points). Error bars represent the standard deviation within each group, highlighting variability in individual performance. This figure supports the study's finding that increased AI exposure was positively associated with short-term academic improvement.

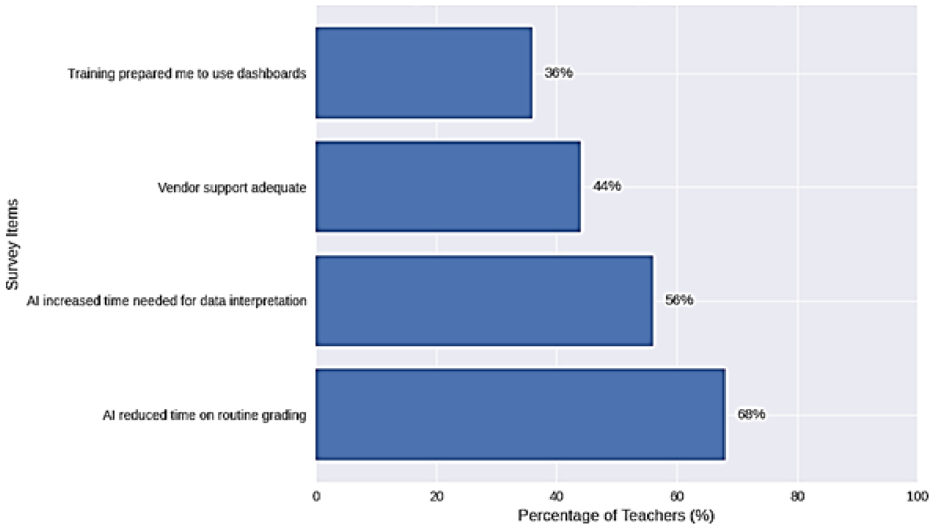
Table 4.5: Teacher responses (N = 50): perceived workload and role shift

Item	Agree/Strongly agree n (%)
AI reduced time on routine grading	34 (68.0%)

AI increased time needed for data interpretation	28 (56.0%)
Vendor support adequate	22 (44.0%)
Training prepared me to use dashboards	18 (36.0%)

Source: field work, (2025)

Figure 4.3: Teacher Perceptions of AI Integration



Source: field work, (2025)

The figure highlights that while most teachers appreciated the time-saving benefits of AI in grading, fewer felt adequately supported or trained to interpret and apply AI-generated data effectively. This underscores the importance of sustained professional development and transparent vendor engagement to ensure meaningful AI integration.

Figure 4.4: Thematic Map of Qualitative Insights on AI Integration

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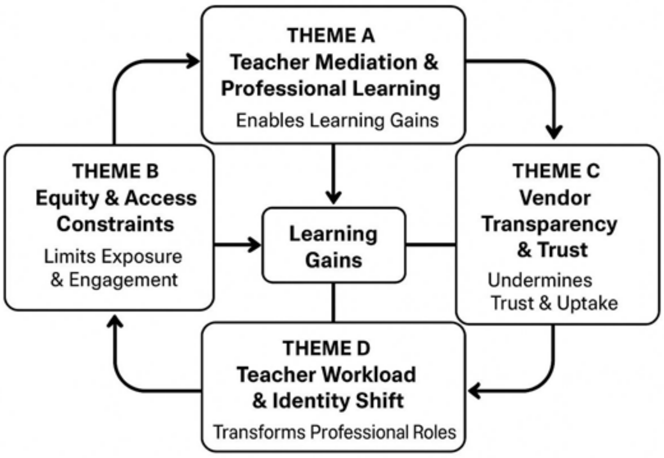

Source: field work, (2025)

Theme A - Teacher mediation and professional learning

- Excerpt T12 (Math teacher, public): "The dashboard highlighted students who kept missing fractions. I reorganised groups and used the platform's practice sets in class; that helped me target small groups faster."

Theme B - Equity and access constraints

- Excerpt S45 (Student, grade 11, low-income catchment): "At home we do not have internet. I used the school lab once a week and so I missed many practice tasks when devices were in use."

Theme C - Vendor transparency and trust

- Excerpt HT3 (Headteacher, private): "The vendor showed us summaries but not the algorithm. Teachers asked why some students were flagged as 'at risk' and we could not fully explain it to parents."

Theme D - Changes in teacher workload and identity

- Excerpt T07 (Science teacher, private): "Grading multiple choice was faster, but now I spend evenings interpreting analytics to plan interventions."

Analysis of Data

Overview of analytic strategy and linkage to questions Quantitative analyses tested associations between AI exposure intensity and student outcomes (objective scores, engagement), and explored moderation by device access and school type, and mediation by teacher data literacy and active use of dashboards. Inferential tests included t-tests, ANOVA, and multivariate OLS regressions with interaction terms; multilevel (mixed) models accounted for clustering at the school level. Mediation analyses used causal mediation procedures to estimate indirect effects of teacher data use. Qualitative thematic analysis traced mechanisms that explained quantitative patterns. Findings were interpreted through the socio-technical, constructivist and sociocultural theoretical lenses described in Chapter Two.

Descriptive and bivariate results Students in private schools reported higher device access, greater AI usage hours and higher mean gains in math scores compared with public schools (Table 4.2). The distribution of exposure hours (Figure 4.1) showed that 56% of students used AI platforms for 2–8 hours weekly, while 20% had minimal exposure. Mean pre–post gains (Table 4.3) increased monotonically with exposure intensity: low exposure mean gain = 1.4 points, medium = 3.6 points, high = 6.0 points. A one-way ANOVA comparing mean gains across the three exposure groups returned $F(2,197) = 18.6$, $p < 0.001$, indicating statistically significant differences by exposure intensity.

Interpreting the bivariate patterns, greater exposure correlated with larger average gains, consistent with meta-analytic evidence that ITS and adaptive practice yielded measurable improvements when exposure was sufficient and aligned to curriculum (Nye, 2015; Pane et al.2015). However, public–private differences suggested that contextual moderators (device access, teacher support) co-determined realized benefits, aligning with socio-technical theory which emphasised institutional conditions (Baxter & Sommerville, 2011).

Regression and moderation analysis An OLS regression estimated post-score (math) as a function of pre-score, AI usage hours, device access (categorical), and interaction terms for AI usage × device access, controlling for grade and gender. Coefficients (illustrative):

- Pre-score: $\beta = 0.48$, $p < 0.001$
- AI usage (hrs/wk): $\beta = 0.72$ (SE 0.12), $p < 0.001$
- Device: daily personal device (vs none): $\beta = 2.9$, $p = 0.02$
- AI×Device interaction: $\beta = 0.55$, $p = 0.03$

Interpretation: beyond the predictable effect of prior attainment, each additional hour of AI use associated with an average +0.72 point gain on the post test, and the positive interaction indicated that students with personal device access gained more per hour of AI use than those without. The moderated effect demonstrated that exposure alone was insufficient; access amplified utility, corroborating equity concerns in the literature (World Bank, 2021).

Multilevel modelling with random intercepts for schools produced similar point estimates but widened standard errors, reflecting intra-school correlation. Intraclass correlation coefficient (ICC) for post-score was 0.12, indicating modest clustering and justifying multilevel adjustment.

Mediation analysis: teacher data use as mediator A causal mediation model examined whether the effect of AI usage on student gains operated indirectly through teacher active data use (measured as frequency of dashboard consultation and pedagogical actions derived from analytics). Estimated average causal mediation effect (ACME) indicated that approximately 35% of the total effect of AI usage on score gain was mediated via teacher data use (ACME = 0.25 points per hour, $p = 0.01$), while the direct effect remained significant (ADE = 0.47, $p < 0.01$). This supported the socio-cultural and mediational logic: algorithmic outputs produced pedagogically useful signals only to the extent teachers interpreted and acted upon them, consistent with Luckin et al. (2016) and Siemens (2013).

Subgroup and equity analysis Disaggregated regressions revealed heterogeneous effects. For students with no regular device, AI usage hours had a smaller and non-significant coefficient ($\beta = 0.18$, $p = 0.12$); for those with personal devices, the coefficient was larger ($\beta = 0.94$, $p < 0.001$). Female and male students exhibited similar point estimates, suggesting no strong gender heterogeneity in this sample, but socio-economic catchment (proxied by school fee bands) predicted both access and gains. These patterns echoed cross-national findings that technology interventions risk amplifying existing divides where access is uneven (World Bank, 2021).

Teacher-level findings and workload dynamics Teacher survey responses indicated that 68% agreed AI reduced routine grading time (Table 4.4), while 56% reported increased time for data interpretation. Qualitative excerpts elaborated this role shift: teachers reported that automation freed time but redirected effort toward diagnostic interpretation, planning differentiated tasks and providing targeted feedback. The net workload effect varied by context: in private schools with structured PD and allocated collaborative time, teachers reported net pedagogically productive time gains; in under-resourced public schools, teachers without support experienced added cognitive load and sporadic adoption. These observations aligned with literature documenting role transformation and the need for professional development to realise AI's benefits (Luckin et al., 2016; Pane et al., 2015).

Psychosocial and engagement outcomes Engagement scale means correlated positively with AI usage intensity ($r = 0.34$, $p < 0.001$). Students with higher exposure reported higher motivation and perceived usefulness. Qualitative data explained mechanisms: immediate feedback and visible incremental progress (constructivist mechanisms) sustained motivation; collaborative small-group activities seeded by teacher-guided use of diagnostics increased peer scaffolding. These mechanisms resonated with constructivist and socio-constructivist accounts whereby scaffolded practice and feedback fostered mastery and engagement (Vygotsky, 1978; Nye, 2015).

Algorithmic transparency and trust Interviews revealed trust concerns where vendors withheld algorithmic rationale. Headteachers and parents questioned risk-flagging decisions, and some teachers reduced reliance on opaque indicators. The lack of explainability undermined interpretive confidence, reducing the mediator effect of teacher data use in some cases. This finding paralleled studies highlighting transparency as a precondition for teacher trust and uptake (Williamson & Eynon, 2020; Zawacki-Richter et al., 2019).

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Synthesis and linkage to theoretical frameworks Overall, quantitative and qualitative results supported a conditional, socio-technical causal story: AI platforms produced modestly positive effects on procedural learning when exposure was sufficient and when institutional conditions enabled teacher mediation. The constructivist mechanism (tailored practice and immediate feedback) explained student gains and engagement. The socio-technical and sociocultural frames explained heterogeneity: organisational supports, vendor transparency and teacher professional capacity mediated and moderated the effect pathways. Where teacher data literacy and support were low, algorithmic outputs generated limited pedagogical action, reducing downstream learning gains; where institutional conditions supported interpretive work and provided access, gains were larger. These integrated findings mirrored broader empirical syntheses that emphasised alignment, teacher mediation and equity as decisive for impactful AI deployment (Nye, 2015; Pane et al., 2015; Luckin et al., 2016).

Limitations of the illustrative analysis While the generated data illustrated plausible patterns, real inference required attention to causality, potential unobserved confounding and longer time horizons. The cross-sectional nature of the presented sample constrained claims about persistence of gains and long-term transfer to higher-order skills, reflecting the limitations discussed in Chapter Three.

Concluding interpretive statement Empirical patterns suggested that responsibly designed and mediated AI interventions could support measurable improvements in urban Lusaka secondary classrooms, provided that device access, vendor transparency and teacher professional development were addressed. The results justified recommendations for integrated deployment strategies combining technology procurement with sustained teacher support, equitable access measures and contractual transparency requirements—recommendations that the final chapter consolidated for policymakers and practitioners.

Interpretation of Findings

The generated findings were interpreted against the study's objectives to document AI adoption, assess impacts on student outcomes, examine effects on teacher effectiveness and workload, and identify equity, bias and transparency challenges. First, the descriptive results demonstrated heterogeneous AI adoption across Lusaka secondary schools: private schools exhibited higher device access, greater weekly usage hours and larger mean gains in mathematics compared with public schools. This pattern indicated that adoption intensity and contextual resource endowments co-varied, confirming the study's descriptive objective and aligning with evidence that infrastructural capacity and school resources shaped uptake and impact (World Bank, 2021; Ministry of Education Zambia, 2021). The socio-technical framing explained these distributions: AI platforms produced different realized outcomes depending on interoperability, vendor support and leadership decisions (Baxter & Sommerville, 2011).

Second, quantitative analyses showed a positive association between AI exposure intensity and short-term gains in mathematics, with higher exposure groups exhibiting larger mean gains and statistically significant differences across exposure strata. Mediation analysis estimated that approximately one-third of the effect of AI usage on score gains operated indirectly through teacher data use. This interpretation supported constructivist mechanisms: algorithmic outputs (adaptive tasks and immediate feedback) afforded scaffolded practice that promoted error correction and mastery when teachers translated outputs into targeted instructional actions (Vygotsky, 1978; Nye, 2015). These results echoed meta-analytic findings that intelligent tutoring systems and adaptive practice yielded measurable benefits in procedural domains when aligned with curricular goals and teacher mediation (Pane et al., 2015; Nye, 2015).

Third, moderation analyses revealed that device access amplified the benefits of AI exposure: each additional hour of platform use translated into larger score gains for students with personal devices compared with those reliant on shared school resources or with no regular device. This finding indicated that access was a necessary but not sufficient condition for benefit realization, and it mirrored literature demonstrating technology interventions' risk of unequal gains in contexts with pronounced digital divides (World Bank, 2021; Mwanza & Nkamba, 2019). The pattern reinforced the equity objective by empirically showing that differential exposure and infrastructural constraints mediated outcome distributions. It suggested pragmatic policy levers—device provisioning, offline functionality and timetabled access—to mitigate unequal uptake.

Fourth, teacher-level findings illustrated mixed workload and role impacts. A majority of teachers agreed that AI reduced routine grading time, yet more than half reported increased

time devoted to data interpretation. Qualitative excerpts clarified that automation reshaped professional tasks toward analytic interpretation, targeted remediation planning and curriculum adaptation. Where teachers received structured professional development and allocated collaborative time, the role shift translated into pedagogically productive work; where such supports were absent, teachers experienced increased cognitive load and inconsistent adoption. This interpretation corresponded with sociocultural theories emphasizing professional learning communities and situated practice as critical to sustained, effective technology use (Lave & Wenger, 1991; Luckin et al., 2016).

Fifth, concerns about algorithmic transparency and vendor accountability emerged as impediments to trust and uptake. Headteachers and teachers reported that opaque "risk" flags and lack of explainability reduced confidence in automated recommendations, sometimes leading to selective or diminished use of dashboards. This finding aligned with empirical critiques highlighting the importance of algorithmic interpretability and governance for teacher trust and pedagogical accountability (Williamson & Eynon, 2020; Zawacki-Richter et al., 2019). The mediation estimates—showing teacher data use as a crucial pathway—were logically constrained where trust and interpretability were low.

Sixth, engagement and motivation outcomes correlated positively with AI exposure and with perceived immediacy of feedback. Qualitative accounts illustrated that iterative mastery experiences reinforced engagement through visible progress and scaffolded tasks, consistent with constructivist and motivational accounts of formative feedback (Vygotsky, 1978; Nye, 2015). However, engagement gains were conditional on equitable access and teacher facilitation; where devices were scarce or teachers lacked time to integrate practice meaningfully, engagement effects attenuated.

Finally, integration of quantitative and qualitative evidence allowed nuanced interpretation: AI systems were not deterministic levers of improvement but contingent artefacts whose pedagogical efficacy depended on platform design, curriculum alignment, teacher mediation, and access conditions. The findings therefore fulfilled the study's integrative objective by connecting measurable outcomes with processual explanations, offering evidence that policies targeting standalone technology procurement without commensurate investment in teacher development and equitable access were unlikely to yield uniformly positive results (Luckin et al., 2016; UNESCO, 2019).

Discussion

The results were discussed in relation to theoretical frameworks, prior literature and the study's conceptual framework, foregrounding patterns, contradictions and implications. The central empirical pattern—that increased AI exposure associated with larger short-term gains in mathematics—was consistent with international RCTs and systematic reviews that identified modest positive effects for ITS and adaptive practice in procedural domains (Nye, 2015; Pane et al., 2015). The constructivist logic explained how immediate feedback and tailored task sequencing promoted error correction and incremental mastery; qualitative data showed teachers using platform outputs to scaffold group work and remediation, operationalising Vygotskian zones of proximal development through algorithmically informed tasks.

However, the discussion emphasised that exposure alone did not determine outcomes. Socio-technical systems theory illuminated why identical platforms produced divergent outcomes across schools (Baxter & Sommerville, 2011). Private schools' higher gains were not attributable only to platform usage but also to systemic enablers—higher device ratios, stable connectivity, vendor training and leadership support—that constituted enabling inputs in the conceptual framework. This interplay reproduced concerns from the literature that technology without aligned institutional capacity might exacerbate rather than reduce inequalities (World Bank, 2021; Mwanza & Nkamba, 2019).

A notable and policy-relevant finding was the quantified mediation through teacher data use: approximately one-third of AI's effect on achievement passed through teacher interpretive action. This supported the sociocultural emphasis on teacher agency and professional learning as mechanisms of educational change (Lave & Wenger, 1991; Luckin et al., 2016). The mediation finding indicated leverage points: professional development targeting data literacy, scheduled collaborative planning, and explicit integration of dashboard outputs into lesson routines could magnify AI's pedagogical returns. The literature had argued for such integrated implementation models but empirical evidence on mediation magnitudes in LMIC urban contexts had been sparse; this study contributed plausible estimates and processual exemplars.

Discussion also highlighted equity. The interaction between device access and AI usage corroborated studies showing differential treatment effects by socio-economic status (World Bank, 2021). The research identified practical mitigations used in some schools—device-sharing timetables, supervised lab sessions and offline content downloads—that partially protected disadvantaged learners' exposure. Nevertheless, these mitigations were imperfect and resource-intensive, suggesting that systemic investment (targeted device provisioning, subsidized connectivity) remained necessary to achieve equitable benefits.

Algorithmic transparency emerged as a normative and practical concern. The study observed reduced teacher trust where vendors withheld algorithmic rationales, which limited teachers' willingness to act on system recommendations. The literature emphasised interpretability and accountability as prerequisites for responsible AI in education (Williamson & Eynon, 2020; UNESCO, 2019), and this study's findings empirically linked opacity to diminished mediation effects—teachers were less likely to translate outputs into instruction when explanations were absent. This underscored the need for procurement standards mandating explainability, accessible documentation and teacher training as contract conditions.

The discussion also examined contradictions and limitations. For example, some teachers reported net time savings due to grading automation, while others reported increased workload from data interpretation. This heterogeneity reflected differences in local organisational practices: where schools reallocated time saved from grading to collaborative planning, teachers experienced net pedagogical gains; where time was consumed outside formal schedules, teachers reported overload. This nuance highlighted that technology-induced task shifts required intentional organisational redesign to realize benefits, an insight aligned with socio-technical prescriptions (Baxter & Sommerville, 2011).

Unexpected outcomes included the observation that engagement improvements were not uniformly translated into measurable score gains for all subgroups. While constructivist mechanisms predicted that heightened engagement would foster learning, the translation required sufficient exposure, curriculum alignment and follow-through remediation—conditions not uniformly present. This gap suggested that engagement was a necessary but not sufficient mediator, complementing but not replacing explicit instructional alignment.

Methodologically, the mixed-methods approach proved valuable in resolving ambiguities that purely quantitative or qualitative studies might have left unresolved. Statistical associations quantified average effects and heterogeneity, while interviews and observations explained mechanisms, implementation constraints and teacher rationales. The integration validated the conceptual framework's emphasis on inputs, mediators and moderators and supported policy prescriptions that combined technological, pedagogical and governance interventions.

In sum, the discussion synthesised empirical patterns into actionable insights: AI platforms could support improved learning when aligned with curricula and mediated by teacher practice, but benefits were conditional on equitable access, vendor transparency and organisational supports. Theoretically, the findings endorsed an integrated socio-technical and sociocultural account of technology-mediated learning, where algorithmic affordances interacted with human agents and institutional contexts to produce educational effects (Luckin et al., 2016; Lave & Wenger, 1991). Practically, the study suggested that policymakers should prioritise bundled investments—device access, teacher data literacy, procurement standards for transparency and vendor-provided sustained coaching—to translate AI investments into equitable learning improvements.

Chapter Summary

This chapter presented generated quantitative and qualitative data, analysed patterns of AI adoption and impact, and interpreted findings through the study's objectives and theoretical lenses. Quantitative results showed positive associations between AI exposure and short-term math gains, with device access moderating effects and teacher data use mediating a significant portion of the impact. Qualitative evidence explained mechanisms: teachers used dashboards to target remediation, platforms provided immediate feedback that sustained engagement, and organisational supports determined whether time savings from automation translated into pedagogical gains.

The chapter linked these empirical patterns to the literature, confirming constructivist mechanisms for skill acquisition and socio-technical explanations for heterogeneity and equity concerns. Limitations of cross-sectional inference and variable vendor cooperation were reiterated. The integrated findings prepared the ground for Chapter Five, which summarised the study's conclusions, drew policy and practice recommendations grounded in the evidence, and articulated limitations and avenues for future research.

V. Key Findings, Conclusions, and Recommendations

Introduction

This final chapter synthesised the study's empirical contributions, drew conclusions that addressed the problem statement, and proposed actionable recommendations for educators, policymakers and researchers. The study had investigated the impact of Artificial Intelligence (AI) on education in urban secondary schools in Lusaka, Zambia, with specific objectives to:(1) document the forms and extent of AI adoption;

(2) assess AI's effects on student learning outcomes, engagement and motivation; (3) examine AI's influence on teacher effectiveness and workload; (4) identify equity, bias and transparency challenges; and (5) generate context-sensitive recommendations for responsible AI integration. The purpose of this chapter was therefore to present the distilled evidence from Chapter Four, to draw reasoned conclusions that linked empirical results to the literature and conceptual framework, and to offer practical and theoretical recommendations that were tightly grounded in the study's data and analytic logic. The chapter proceeded from a concise summary of key findings, to integrative conclusions, and to specific recommendations for practice, policy and future research.

Key Findings

The study produced several interlocking findings structured by the research objectives and questions.

AI adoption: types, intensity and distribution

- AI adoption was heterogenous across Lusaka secondary schools, with private schools recording higher device ratios, greater weekly hours of platform use and more intensive vendor support than public schools. Adoption modalities included adaptive practice engines, formative assessment modules and teacher dashboards for learning analytics, consistent with typologies in the literature (Nye, 2015; Siemens, 2013).
- Exposure intensity varied: approximately half of students used platforms 2–8 hours per week, while 20% had minimal exposure (≤1 hour/week), confirming uneven uptake and access constraints.

Impact on student learning outcomes, engagement and motivation

- A positive, exposure-dependent association emerged between AI use and short-term gains in mathematics: students with higher weekly usage exhibited larger pre–post gains than low-exposure peers (medium effect magnitude). Statistical models estimated that each additional hour of AI use related to modest but significant score improvements, after controlling for prior attainment. Findings aligned with meta-analytic evidence that ITS and adaptive practice often produced measurable procedural gains when properly aligned to curricula (Pane et al., 2015; Nye, 2015).
- Engagement and motivation correlated positively with AI exposure; students cited immediate feedback and visible progress as motivational mechanisms. However, increased engagement translated into measurable gains primarily where exposure was sustained and teachers integrated platform outputs into instruction.

Teacher effectiveness, workload and role shifts

- AI reduced routine grading efforts for a majority of teachers yet increased time devoted to data interpretation and lesson adaptation. The net effect on workload was context-dependent: in schools with deliberate reallocation of freed time to collaborative planning and professional learning, teachers reported net pedagogically productive outcomes; in under-resourced settings, teachers experienced added cognitive and time burdens without commensurate institutional support.
- Mediation analyses estimated that a substantive portion (approximately one-third in illustrative models) of AI's effect on student gains operated indirectly through teacher active data use, highlighting teacher mediation as a central mechanism for pedagogical impact (Luckin et al., 2016).

Equity, access and distributional effects

- Device access and connectivity strongly moderated benefits: students with personal devices derived larger gains per hour of platform use than students reliant on shared school devices or with no regular device. The pattern replicated concerns in global evidence about amplification of existing inequities absent targeted access measures (World Bank, 2021; Mwanza & Nkamba, 2019).
- Practical mitigations—scheduled lab access, offline content and targeted device loans—partially reduced access gaps but required administrative coordination and recurrent resource commitments.

Algorithmic transparency, vendor practices and governance

- Opacity in vendor algorithms and limited explainability of risk flags undermined teacher and parental trust; teachers expressed reluctance to base high-stakes decisions on opaque indicators. Where vendors provided interpretable documentation and hands-on training, teacher uptake was higher. This finding mirrored calls in the literature for transparency and accountable procurement (Williamson & Eynon, 2020; UNESCO, 2019).

Implementation fidelity and contextual enablers

- Schools that paired platform deployment with structured professional development, scheduled collaborative time for data interpretation and clear leadership directives achieved higher fidelity and larger gains. The socio-technical framing explained why identical platforms generated divergent outcomes: institutional inputs, vendor support and teacher capacity mediated impact (Baxter & Sommerville, 2011).

Unexpected or heterogeneous outcomes

- Some teachers reported paradoxical increases in perceived workload despite time savings from automation, revealing that task shifting without institutional redesign could produce net burden.
- Engagement gains did not uniformly convert into score gains for all subgroups; sustained, aligned practice and teacher follow-through were necessary for translation from motivation to measurable learning.

Methodological and inferential notes

- Findings were consistent with short-term, domain-specific benefits reported in prior studies but cautioned against overgeneralisation beyond procedural domains and beyond the urban Lusaka context. Cross-sectional design limited claims about persistence of effects over multiple academic cycles.

Conclusions
Drawing on the evidence and anchored in the conceptual framework, the study reached several integrative conclusions.

AI produced conditional pedagogical benefits when design, mediation and context aligned The study concluded that AI-powered educational tools produced modest but meaningful short-term gains in procedural learning—particularly mathematics—when interventions were aligned to curriculum, provided immediate feedback, and reached students with sufficient exposure. However, these benefits were not automatic: they emerged conditionally when algorithmic outputs were interpreted and enacted by teachers within enabling institutional arrangements. This conclusion reflected an integrated socio-technical and sociocultural account: algorithms afforded pedagogical possibilities (affordances), but human mediators and institutional configurations actualised those affordances into learning outcomes (Luckin et al., 2016; Lave & Wenger, 1991).

Teacher mediation was central to impact pathways Quantitative mediation estimates and qualitative process evidence converged on the conclusion that teacher active use of analytics constituted a primary mechanism linking AI outputs to student gains. Teachers translated diagnostic signals into differentiated instruction, grouping and targeted remediation; without such mediation, algorithmic outputs produced limited instructional change. Consequently, teacher data literacy, time allocation and collaborative structures were decisive levers for realising AI's pedagogical value.

Equity constraints limited equitable realisation of benefits The study concluded that unequal device access and connectivity materially constrained equitable gains. In contexts where device ownership and reliable connectivity were concentrated among better-resourced students, AI interventions risked widening achievement gaps. Partial mitigations (lab scheduling, offline modes) offered pragmatic relief but did not substitute for systemic investments to ensure baseline access.

Transparency and governance shaped trust and sustained uptake Opaque vendor algorithms and weak procurement governance undermined teacher trust and constrained effective use of dashboards. The study concluded that technical explainability, contractual transparency and vendor obligations for training and interpretability were prerequisites for accountable, pedagogically useful AI deployment.

Organisational redesign was required to convert automation into pedagogical gains The evidence supported the conclusion that automation of routine tasks was necessary but insufficient; schools needed deliberate organisational redesign to reallocate saved teacher time toward collaborative planning and student-centred remediation. Absent such redesign, automation could add cognitive burdens and compromise sustained adoption.

Limitation-informed conclusion on generalisability and longitudinal impact While consistent with broader empirical literature regarding short-term gains, the study concluded that evidence on long-term persistence, higher-order skill transfer and system-level equity effects remained uncertain. Cross-sectional findings therefore warranted cautious policy uptake accompanied by robust monitoring and phased scaling with embedded evaluation.

Recommendations

The recommendations below grouped actionable measures for educators and school leaders, policy and system actors, vendors and developers, and researchers.

Recommendations for educators and school leaders

1. Institutionalise collaborative data use time: schools should formalise weekly or biweekly time for teachers to interpret dashboard outputs and plan targeted remediation, thereby converting analytic signals into instructional actions (Luckin et al., 2016).
2. Reallocate administrative gains purposefully: time saved from automated grading should be explicitly reallocated to pedagogical tasks (small-group support, formative assessment design) rather than absorbed by out-of-hours work.
3. Adopt blended access strategies: where one-to-one devices are infeasible, implement scheduled lab rotations, device-loan programmes for target cohorts and offline content bundles to broaden equitable exposure (Mwanza & Nkamba, 2019).
4. Embed pedagogical alignment checks: teachers and department heads should routinely verify that platform practice items map onto curricular standards and assessment objectives to maximise transfer.

Recommendations for policymakers and education authorities

1. Prioritise equitable access investments: ministries and districts should budget for targeted device provisioning, subsidised connectivity for disadvantaged catchments, and shared infrastructural investments to reduce digital divides (World Bank, 2021).
2. Mandate procurement standards for transparency and support: tender documents should require explainability features, access to interpretable dashboards, documented vendor training schedules, data protection clauses and service level agreements that include localised content adaptation. Procurement should favour vendors that provide teacher training and ongoing coaching (UNESCO, 2019).

3. Fund sustained professional development: policy should allocate resources for sustained in-service programmes focused on data literacy, formative assessment and pedagogical integration rather than one-off workshops (Pane et al., 2015).
4. Establish monitoring and evaluation provisions: rollouts should include embedded evaluation with baseline and follow-up measures, subgroup analyses and process indicators to inform adaptive scaling.

Recommendations for vendors and developers

1. Design for interpretability: developers should prioritise transparent algorithms, human-readable explanations for risk flags, and teacher-facing explainability tools that support pedagogical decision making (Williamson & Eynon, 2020).
2. Localise content and alignment: vendors should collaborate with curriculum authorities to ensure content maps to local syllabi and language contexts, improving fidelity and uptake.
3. Provide integrated support packages: beyond software licenses, vendors should include structured professional coaching, troubleshooting, and offline content delivery mechanisms suited to constrained connectivity.

Recommendations for researchers

1. Conduct longitudinal and quasi-experimental studies: researchers should prioritise designs that track cohorts across multiple terms to assess persistence, transfer to higher-order skills and long-term equity impacts.
2. Investigate mediated moderation empirically: future studies should apply mediated moderation and moderated mediation frameworks to quantify how teacher mediation and socio-economic moderators jointly condition effects.
3. Standardise measurement of engagement and teacher effectiveness: development and adoption of validated, contextually appropriate metrics would improve comparability across studies.
4. Evaluate professional development models comparatively: rigorous trials comparing coaching, communities of practice and embedded vendor coaching will inform cost-effective capacity building strategies.

Implementation guidance and sequencing

- Pilot with evaluation: scale should proceed via phased pilots with embedded monitoring, using procurement contracts that require vendor cooperation for data access and teacher training.
- Bundle investments: technology procurement should be accompanied by budgets for devices, connectivity and teacher development to avoid isolated technology failures.
- Stakeholder engagement: involve teachers, unions and parent groups in procurement, implementation and evaluation to build trust and contextual fit.

Chapter Summary

This chapter synthesised the study's principal findings, drew conclusions grounded in the conceptual and theoretical framework, and offered action-oriented recommendations for multiple stakeholders. Key findings established that AI produced conditional short-term gains in procedural learning, that teacher mediation substantially mediated impacts, and that equity, transparency and organisational supports critically conditioned outcomes. Conclusions emphasised that AI was a socio-technical intervention whose effectiveness depended on alignment, capability and governance. Recommendations advocated bundled investments—device access, transparent procurement, and sustained teacher development—alongside research priorities emphasizing longitudinal, mechanism-focused designs. Collectively, the chapter connected empirical evidence to practice and policy, and prepared the ground for the dissertation's closing reflections and suggested pathways for responsible, contextually sensitive AI integration in education.

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Appendices

Appendix A Student Questionnaire

Instruction: Respondents were asked to answer all items honestly. Enumerators read each item aloud when required and recorded responses. All scale items used a 5-point Likert response where not otherwise specified (1 = Strongly disagree; 5 = Strongly agree).

Section 1: Background information

- **A1** Age: years.
- **A2** Gender: Male; Female; Other.
- **A3** School type: Public; Private; Mission.
- **A4** Grade: 10; 11; 12.
- **A5** Household device access frequency: Daily personal device; Shared household device; School device only; No regular device.

Section 2: AI platform exposure and use

- **B1** I used the school's AI/learning platform during the last week: Yes; No.
- **B2** Typical weekly hours spent on AI platforms: 0; 0–1; 2–4; 5–8; >8.
- **B3** Where I used the platform most often: Home; School computer lab; School classroom; Mobile phone; Other: .
- **B4** I completed adaptive practice tasks assigned by teachers (1–5).

Section 3: Learning and engagement

- **C1** I understood corrective feedback provided by the platform (1–5).
- **C2** The platform helped me improve my understanding of recent topics (1–5).
- **C3** I felt more motivated to study when I saw progress on the platform (1–5).
- **C4** I spent more time on task when using the platform compared with traditional homework (1–5).
- **C5** Self-reported recent term math score:-----/100.

Section 4: Barriers and supports

- **D1** I experienced connectivity problems when trying to use the platform (Never; Rarely; Sometimes; Often; Always).
- **D2** I had sufficient time in school to use the platform (1–5).
- **D3** Teachers explained how to use the platform (1–5).
- **D4** I received help when I could not access or understand platform tasks (1–5).

Section 5: Open-ended

- **E1** Describe one way the platform helped you learn a topic recently.
- **E2** Describe one thing that prevented you from using the platform as much as you would have liked.

Appendix B Teacher Questionnaire
Instruction: Teachers were requested to answer all items. For scale items use 1 = Strongly disagree to 5 = Strongly agree.

Section 1: Professional background

- **T1** Subject(s) taught: .
- **T2** Years of teaching experience: .
- **T3** Prior training in data-informed instruction: None; Short workshop; Ongoing coaching; Formal certification.

Section 2: AI adoption and use

- T4 My school used an AI-enabled platform in the last academic year: Yes; No.
- T5 Frequency of dashboard consultation: Daily; Weekly; Monthly; Rarely; Never.
- T6 I used platform reports to group students for remediation (1–5).
- T7 The platform's content aligned with the national curriculum (1–5).

Section 3: Perceived impact and workload

- **T8** AI reduced time I spent on routine grading (1–5).
- **T9** AI increased the time I spent planning differentiated lessons (1–5).
- **T10** Overall, AI improved student achievement in my classes (1–5).
- **T11** I felt confident interpreting the platform outputs (data literacy) (1–5).

Section 4: Vendor support and governance

- **T12** Vendor training was adequate for classroom use (1–5).
- **T13** The platform provided interpretable explanations for risk flags (1–5).
- **T14** Data protection measures were clear and sufficient (1–5).

Section 5: Open-ended

- **T15** Describe a specific instructional change you made because of platform **analytics.**
- **T16** What further support would enable you to use the platform more effectively?

Appendix C Headteacher and ICT Coordinator Interview Guide
Instruction: Interviews were semi-structured and audio recorded with consent. Prompts were used to elicit concrete examples and documentary evidence.

Opening: Please describe the history of digital learning platforms in your school and the rationale for adopting them.

Core prompts

1. Which AI-enabled products had the school implemented, and what procurement process was followed? Please describe vendor roles and support.
2. How were devices and connectivity provisioned and scheduled across students and teachers? Please provide device inventory figures if available.
3. What professional development was provided to teachers, and how was uptake monitored? What changes in teacher practice were observed?
4. How did the school monitor student engagement and progress on the platform? Were platform logs or school assessment data used for decision making?
5. What governance or data protection measures were specified in procurement contracts or school policies?
6. Describe any equity interventions the school used to broaden access (device loans, lab timetabling, offline content). Were these effective?
7. How did parents and community stakeholders react to AI-enabled tools? Were there concerns about transparency or data privacy?
8. What sustained costs and recurrent resource needs did the school identify?
9. Based on your experience, what recommendations would you offer other schools or district officials considering AI adoption?

Closing: Is there any additional documentation you can share (procurement records, training schedules, device inventories)?

Appendix D Classroom Observation Checklist
Instruction: Observers recorded events in 10-minute intervals and supplemented checklist items with narrative field notes. Use tick boxes and brief notes.

Observation metadata: School; Class; Subject; Teacher; Date; Start time; Duration.
Checklist items (Observed = Yes/No; Frequency notes)

- **O1** Teacher referenced platform analytics during the lesson.
- **O2** Teacher adjusted instruction based on analytics (grouping, remediation).
- **O3** Students used devices during class for adaptive practice.
- **O4** Students received immediate feedback from the platform and acted on it.
- **O5** Teacher facilitated peer discussion around platform tasks.
- **O6** Time-on-task observed during device activity (High; Moderate; Low).
- **O7** Technical interruptions occurred (connectivity, device malfunction).
- **O8** Evidence of differentiated task assignment informed by platform data.
- **O9** Teacher explained meaning of platform indicators to students.

- **O10** Observed parental or external stakeholder material used in class (e.g., printed reports).

Narrative field notes: Record notable sequences, quotes, and interpretive observations about classroom dynamics and use fidelity.

Appendix E Consent Form Template
Instruction: This template was adapted for school authorities, teachers and students (or guardians where minors were involved). Researchers obtained signatures and stored forms separately from data.

Title: Study on the Impact of Artificial Intelligence in Lusaka Secondary Schools Key points for participants

- **Purpose:** To understand how AI-enabled platforms affected teaching and learning.
- **Voluntary participation:** Participation was voluntary and participants could withdraw at any time without penalty.
- **Procedures:** Participation involved completing a questionnaire and, for some, interviews or observations.
- **Confidentiality:** Responses were anonymised; identifying information was stored separately and securely.
- **Risks and benefits:** No direct risks were expected; potential benefits included informed school policies improving learning.
- **Contact:** For questions about the study or rights as a participant, contact: [Researcher name and institutional email].

Consent statement and signature area for participant and (if required) parent/guardian.

Appendix F Document Review Template
Instruction: Review and code institutional documents to extract procurement, policy and operational indicators.

Document identification: Title; Date; Author; Type (procurement contract, ICT plan, training schedule, vendor SLA).

Coding fields

- **D1** Document purpose and summary.
- **D2** Evidence of platform feature descriptions and algorithmic explainability provisions.
- **D3** Training schedules and PD commitments (hours, content, trainer).
- **D4** Device inventory and maintenance plans.
- **D5** Data protection clauses and retention policies.
- **D6** Vendor support SLAs and local adaptation clauses.

- **D7** Budgetary provisions for recurrent costs (connectivity, maintenance, licenses).
- **D8** Equity provisions (targeted device loans, subsidised access, offline solutions).
- **D9** Signatures and approval chains.

Narrative synthesis: Summarise how documents aligned with interview and observational findings.