
LEADING THE AI-ENABLED SCHOOL HOW PRINCIPALS' AI LITERACY AND ETHICAL LEADERSHIP SHAPE TEACHERS' GENERATIVE AI ADOPTION AND INSTRUCTIONAL INNOVATION

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ABSTRACT

Generative artificial intelligence (GenAI) is moving rapidly from experimentation into teachers' everyday planning, assessment, resource creation and instructional decision-making, yet adoption remains uneven and ethically contested in K–12 schools. Existing research has concentrated primarily on teacher-level acceptance, preparedness and AI literacy, leaving limited multilevel evidence on how school leaders' own AI competence and ethical leadership shape teachers' classroom use of GenAI and the translation of that use into instructional innovation. This study develops a multilevel model that positions principal AI literacy and ethical leadership as school-level antecedents, teacher GenAI adoption as a teacher-level mediating mechanism, and instructional innovation as the downstream pedagogical outcome. The study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and Social Learning Theory. A matched principal–teacher quantitative design is proposed for licensed Montessori and Montessori-oriented private schools in Greater Accra, Ghana. The target design is at least 60 school clusters, one principal per school and approximately eight to ten teachers per school. Principal AI literacy will be measured from principal reports, ethical leadership from aggregated teacher ratings, and GenAI adoption and instructional innovation from teacher responses collected in two waves. Multilevel structural equation modelling will be used to evaluate measurement quality, between-school variance, direct cross-level effects and indirect effects through teacher GenAI adoption. The study is designed to contribute to educational leadership and AI-in-education

research by showing whether technologically literate and ethically credible principals create school conditions in which teachers not only adopt GenAI but convert it into responsible instructional innovation.

KEYWORDS: Principal Ai Literacy; Ethical Leadership; Generative Ai Adoption; Instructional Innovation; Multilevel Structural Equation Modelling; Montessori Schools; Ghana.

INTRODUCTION

Generative artificial intelligence has become one of the most consequential digital developments confronting schools because it can produce text, images, explanations, feedback, lesson materials and assessment resources at a speed and scale that changes teachers' work. UNESCO's global guidance emphasises that the educational value of GenAI depends on human-centred design, protection of learner rights, data privacy, age appropriateness and the preservation of human agency, while its 2024 AI Competency Framework for Teachers argues that educators require competence in AI foundations, ethics, pedagogy and professional learning rather than simple tool familiarity (Miao & Holmes, 2023; Miao & Cukurova, 2024). Recent K–12 studies similarly show that teachers use GenAI for lesson preparation, assessment, administrative tasks and learning activities, but integration remains uneven because preparedness, policy guidance, perceived value and ethical concerns differ substantially across teachers and schools (Cheah et al., 2025; Collie & Martin, 2024).

The unevenness of adoption has shifted the problem from whether GenAI is available to whether schools possess the leadership capacity to turn it into pedagogically responsible practice. Teacher adoption studies increasingly recognise institutional support, credible information, professional development and leadership climate as important determinants of AI acceptance. Hazzan-Bishara et al. (2025), for example, found that institutional support influenced teachers' intention to use GenAI both directly and indirectly through motivation and self-efficacy. Collie and Martin (2024) likewise showed that autonomy-supportive leadership was associated with teachers' valuing of GenAI, which in turn predicted integration in teaching-related work and student learning activities. These findings suggest that teacher-level attitudes cannot be understood apart from the school-level conditions created by leaders.

Two leadership capabilities are especially relevant. The first is principal AI literacy: the capacity to understand what AI systems can and cannot do, use and evaluate them

competently, recognise ethical risks and make informed decisions about their educational application. AI literacy has been conceptualised through dimensions such as awareness, use, evaluation and ethics (Wang et al., 2023), while UNESCO's framework adds human-centred mindset, AI pedagogy and professional learning to the competence expected of educators (Miao & Cukurova, 2024). A principal who lacks these capabilities may struggle to distinguish productive AI use from hype, design meaningful professional development, select suitable tools, or guide teachers through implementation problems. A technologically literate principal, in contrast, can act as a credible source of information and a knowledgeable sponsor of experimentation.

The second capability is ethical leadership. GenAI adoption in schools raises questions about student privacy, bias, hallucinated information, copyright, academic integrity, transparency, over-reliance on automated outputs, commercial vendor dependence and the preservation of teacher and learner autonomy. A recent synthesis of 62 K–12 studies concludes that principals increasingly operate as socio-technical stewards who must balance efficiency with equity, human oversight, data protection and professional autonomy (Ho, 2026). Ethical leadership is therefore not peripheral to AI implementation. It can create trust, fairness and psychological safety, clarify acceptable boundaries and make teachers more willing to experiment responsibly. A meta-analysis of 47 educational studies involving 18,423 participants found that principals' ethical leadership has strong positive relationships with teacher trust, justice, satisfaction, motivation and commitment (Özdoğan & Sarier, 2024).

The Ghanaian setting makes these questions especially timely. Recent evidence indicates that basic-school teachers in Ghana possess moderate rather than uniformly high AI literacy across knowledge, application, evaluation and ethics, and newer structural modelling work shows that these dimensions are interdependent rather than interchangeable (Arkorful et al., 2025; Arkorful et al., 2026). These studies provide valuable teacher-level evidence, but they do not explain how principals' own AI competence or ethical leadership shapes adoption across schools. At the same time, Ghana's private pre-tertiary sector is large and organisationally diverse. The National Schools Inspectorate Authority (NaSIA) reported 855 licensed private schools in Greater Accra in the first quarter of 2025 and is mandated to license and regulate public and private pre-tertiary institutions, providing a viable institutional frame for school-level research (NaSIA, 2025).

Montessori and Montessori-oriented schools provide a theoretically useful context for the study because their pedagogical identity emphasises learner autonomy, differentiated learning, observation, carefully designed learning environments and the teacher's role as a

guide rather than a transmitter of uniform content (Lillard, 2017). GenAI may support personalised resource design, differentiated prompts, teacher planning and formative feedback, but it may also conflict with developmental appropriateness, independent thinking and hands-on learning if used without pedagogical judgement. The setting therefore makes the combination of AI literacy and ethical leadership especially consequential: principals must understand the technology while safeguarding the human-centred pedagogical principles on which instructional decisions rest (Miao & Cukurova, 2024; UNESCO, 2023).

Despite the growing literature, four gaps remain. First, most studies focus on teachers' individual AI literacy, motivation, self-efficacy, perceived usefulness or intention to use GenAI rather than on the competence of school principals as an antecedent of teacher adoption (Arkorful et al., 2025; Hazzan-Bishara et al., 2025). Second, ethical leadership has been linked to trust, commitment and digital pedagogical agency, but there is little multilevel empirical evidence connecting principals' ethical conduct specifically to teachers' GenAI adoption and instructional innovation (Ho, 2026; Mphatsoane-Sesoane & Jita, 2025). Third, many AI-in-education studies analyse teachers as statistically independent even though teachers are nested within schools and share common leadership, policies and infrastructure. Fourth, evidence from African K–12 contexts remains limited, despite distinctive institutional, infrastructural and professional-development conditions that can affect both AI adoption and leadership effectiveness (Arkorful et al., 2026; UNESCO, 2024).

This study addresses these gaps by developing a multilevel model in which principal AI literacy and ethical leadership operate at the school level, teacher GenAI adoption functions as a cross-level mediating mechanism, and instructional innovation is the teacher-level outcome. The study advances the literature in four ways. It shifts attention from teachers' AI readiness alone to the competence and ethical behaviour of school leaders; it integrates technology-adoption and social-learning explanations across levels of analysis; it tests whether teacher GenAI adoption is the mechanism through which leadership becomes pedagogical innovation; and it provides context-specific evidence from Montessori and Montessori-oriented schools in Greater Accra. This move mirrors a broader insight from organisational AI research: technology adoption alone does not guarantee valuable outcomes; leadership determines whether technological capability is translated into effective practice (Marfo et al., 2026).

Theoretical Foundation

The study is anchored in the Unified Theory of Acceptance and Use of Technology (UTAUT) and Social Learning Theory. UTAUT explains technology adoption through performance expectancy, effort expectancy, social influence and facilitating conditions, with behavioural intention and use shaped by both individual and contextual conditions (Venkatesh et al., 2003). The framework is appropriate for GenAI in schools because teachers exercise substantial instructional autonomy but do so within environments where leadership, professional norms, access to tools, technical support and school expectations shape whether adoption is feasible and valued. Recent teacher-AI studies reinforce the importance of external support, credible information and organisational conditions in extending individual-level technology-acceptance models (Hazzan-Bishara et al., 2025; Collie & Martin, 2024).

Social Learning Theory explains how individuals learn appropriate behaviours by observing credible role models, interpreting behavioural consequences and internalising social norms (Bandura, 1977). Ethical leadership research applies this logic to organisations by arguing that leaders influence followers through visible moral conduct, communication, reinforcement and fair decision-making (Brown et al., 2005). In an AI-enabled school, principals communicate not only whether AI should be used, but how responsibly it should be used. Their behaviour signals whether experimentation is supported, whether mistakes can be discussed openly, whether data privacy and fairness matter, and whether professional judgement should remain central when automated tools are introduced (Ho, 2026; Özdoğan & Sarier, 2024).

The two theories address different parts of the proposed process. UTAUT explains why a supportive school environment and credible leadership can make teachers more willing and able to use GenAI, while Social Learning Theory explains why the principal's competence and ethical behaviour become socially meaningful cues that shape teacher action. Principal AI literacy contributes to the facilitating conditions and informational credibility surrounding GenAI; ethical leadership supplies the normative trust and modelling through which responsible adoption becomes legitimate. Teacher GenAI adoption then becomes the behavioural mechanism through which these school-level conditions are translated into instructional innovation (Cheah et al., 2025; Mphatsoane-Sesoane & Jita, 2025).

Theoretical Integration Justification

UTAUT is strong in explaining acceptance and use but is less explicit about the quality of leadership that creates the social influence and facilitating conditions surrounding

technology. Social Learning Theory addresses this limitation by explaining how principals become behavioural and moral reference points for teachers. Conversely, Social Learning Theory explains modelling and normative influence but does not specify the technology-specific conditions that make adoption easier, useful or institutionally supported. Combining the two therefore provides a stronger multilevel explanation than either theory alone: leader competence and ethics shape the school environment, that environment influences teacher GenAI adoption, and adoption enables new instructional practices (Venkatesh et al., 2003; Brown et al., 2005; Hazzan-Bishara et al., 2025).

Alternative theories were considered but are less suitable for the specific model. The Technology Acceptance Model offers a parsimonious account of perceived usefulness and ease of use but gives less explicit attention to school-level social influence and facilitating conditions. The Technology–Organization–Environment framework captures organisational context but does not explain teacher-level adoption mechanisms or leader role modelling. Diffusion of Innovations explains how innovations spread but offers less precision for ethical leadership and nested mediation. The combined UTAUT–Social Learning perspective is therefore better aligned with a model in which principal characteristics operate at Level 2 while adoption and instructional innovation occur at Level 1 (Venkatesh et al., 2003; Bandura, 1977; Ho, 2026).

Empirical Review and Hypotheses Development

Principal AI Literacy and Teachers' Generative AI Adoption

AI literacy is more than the ability to prompt a chatbot. Validated measurement work identifies awareness, use, evaluation and ethics as core components, while education-focused frameworks add pedagogical judgement, human-centred values and professional learning (Wang et al., 2023; Miao & Cukurova, 2024). In school leadership, these competencies influence the principal's capacity to interpret vendor claims, identify age-appropriate uses, distinguish hallucinated or biased outputs, support teacher learning and make credible decisions about AI-enabled teaching. Where principals understand GenAI deeply, their guidance is more likely to be perceived as informed rather than symbolic.

Evidence increasingly shows that contextual support matters for teacher adoption. Hazzan-Bishara et al. (2025) found that institutional support had direct and indirect relationships with teachers' intentions to use GenAI, while Collie and Martin (2024) found that leadership context was associated with teachers' GenAI valuing and subsequent integration. Ghanaian studies show that teacher AI literacy is still developing, making knowledgeable school-level

guidance especially important (Arkorful et al., 2025; Arkorful et al., 2026). A principal with higher AI literacy should therefore be better able to create usable policies, identify appropriate tools, organise targeted professional learning and reduce uncertainty around instructional adoption. Hence:

H1: Principal AI literacy has a positive and significant cross-level effect on teachers' Generative AI adoption.

Ethical Leadership and Teachers' Generative AI Adoption

Ethical leadership refers to normatively appropriate personal conduct and the active promotion of ethical behaviour through communication, reinforcement and decision-making (Brown et al., 2005). In schools, ethical principals are associated with stronger organisational trust, justice, motivation and commitment, suggesting that ethical conduct shapes the psychological climate in which teachers respond to change (Özdoğru & Sarier, 2024). This is particularly relevant for GenAI because teachers face uncertainty about privacy, copyright, bias, academic integrity, student dependency and accountability for AI-generated content (Ho, 2026; Miao & Holmes, 2023).

Ethical leaders can make adoption safer by setting transparent expectations, involving teachers in policy formation, protecting professional judgement, communicating data-protection boundaries and treating early experimentation as a learning process rather than a compliance test. Recent work on digital pedagogical innovation argues that ethical leadership supports teacher agency by creating trust, equity and collaborative professional space, whereas technocratic leadership can reduce teachers to implementers of digital directives (Mphatsoane-Sesoane & Jita, 2025). In this sense, ethical leadership should reduce perceived social and moral risk while increasing legitimate support for responsible experimentation. Hence:

H2: Principal ethical leadership has a positive and significant cross-level effect on teachers' Generative AI adoption.

Teachers' Generative AI Adoption and Instructional Innovation

Instructional innovation involves the generation, promotion and implementation of new ideas that improve teaching, learning, assessment or classroom organisation. Innovation is therefore broader than creativity because it requires ideas to be enacted in practice (Janssen, 2000). Teacher-focused validation studies show that innovative behaviour can be meaningfully measured in educational settings and is particularly important in systems where

teachers must respond to diverse learner needs and changing instructional demands (Kuril et al., 2023; Hosseini et al., 2021).

GenAI expands the resources teachers can use to generate and test new instructional ideas. It can support differentiated lesson planning, multilingual resource creation, formative assessment, feedback, examples, scenarios, simulations and rapid adaptation of materials. UNESCO's teacher competency framework explicitly identifies AI-enhanced pedagogical innovation as an advanced competence, but stresses that technology should support rather than undermine human agency, critical thinking and learner autonomy (Miao & Cukurova, 2024). K–12 evidence shows that teachers already use GenAI for planning and assessment, although many have not yet moved from productivity-oriented use to deeper classroom integration (Cheah et al., 2025). Adoption should therefore increase the behavioural opportunity for instructional innovation when teachers use AI as a pedagogical resource rather than merely an administrative shortcut. Hence:

H3: Teachers' Generative AI adoption has a positive and significant effect on instructional innovation.

Principal AI Literacy and Instructional Innovation

Principal AI literacy may influence instructional innovation beyond its effect on adoption. A knowledgeable leader can recognise promising instructional applications, allocate time for experimentation, connect teachers to suitable professional learning, evaluate risks without defaulting to prohibition and ask better questions about the pedagogical value of AI-generated materials. The principal's competence can therefore become an organisational resource that shapes whether technology is used superficially or incorporated into deeper instructional redesign (Miao & Cukurova, 2024; Ho, 2026).

This relationship is particularly relevant in Montessori-oriented environments, where instructional innovation must remain consistent with learner autonomy, developmental appropriateness and purposeful teacher observation. A principal who understands both AI capability and pedagogical limits is better positioned to support teachers in using GenAI for preparation, differentiation and reflection without allowing automated output to displace hands-on learning or teacher judgement. Thus:

H4: Principal AI literacy has a positive and significant cross-level effect on teachers' instructional innovation.

Ethical Leadership and Instructional Innovation

Innovation involves uncertainty and the possibility of failure. Teachers are more likely to propose, test and refine new practices when they believe leaders will treat them fairly, listen to professional concerns and distinguish responsible experimentation from misconduct. Ethical leadership can therefore provide the trust and psychological safety necessary for innovation. Meta-analytic educational evidence shows strong links between ethical leadership and teacher trust, motivation and commitment, while broader organisational research connects ethical leadership with innovative work behaviour through supportive and empowering mechanisms (Özdoğan & Sarier, 2024; Mphatsoane-Sesoane & Jita, 2025).

In the GenAI context, ethical leadership may also improve the quality of innovation by preventing speed and novelty from becoming the only criteria for technology use. Human oversight, fairness, privacy, inclusion and accountability can help teachers innovate within clear moral boundaries rather than avoid GenAI because of uncertainty or use it uncritically because of managerial pressure (Ho, 2026; Miao & Holmes, 2023). Hence:

H5: Principal ethical leadership has a positive and significant cross-level effect on teachers' instructional innovation.

The Mediating Role of Teachers' Generative AI Adoption

The proposed model treats teacher GenAI adoption as the behavioural bridge between school-level leadership and instructional innovation. Principal AI literacy can create credible guidance and enabling conditions, but innovation will not follow if teachers do not actually incorporate GenAI into their professional practice. This logic is consistent with technology-adoption research showing that contextual support exerts value through teacher motivation, acceptance and use, and with organisational AI studies showing that technological capabilities create outcomes only when they are actively deployed (Hazzan-Bishara et al., 2025; Marfo et al., 2026).

The same mechanism applies to ethical leadership. Ethical conduct does not directly generate new lesson plans or assessment strategies; rather, it can create a trusted environment in which teachers feel able to adopt GenAI responsibly, discuss risks and experiment with new practices. When responsible adoption increases, the repertoire of instructional options expands and innovation becomes more likely. This mediation argument links Social Learning Theory to UTAUT by locating the behavioural mechanism between leader context and

pedagogical outcome (Brown et al., 2005; Venkatesh et al., 2003; Collie & Martin, 2024). Hence:

H6: Teachers' Generative AI adoption mediates the positive relationship between principal AI literacy and instructional innovation.

H7: Teachers' Generative AI adoption mediates the positive relationship between principal ethical leadership and instructional innovation.

Conceptual Framework

The conceptual framework proposes a 2-1-1 multilevel mediation structure. Principal AI literacy is measured from the principal and treated as a school-level predictor. Ethical leadership is measured from teacher ratings of the principal and represented at the school level after multilevel measurement and aggregation checks. Teacher GenAI adoption and instructional innovation are Level-1 constructs. The direct paths test whether leadership capabilities shape adoption and innovation, while H6 and H7 test whether adoption transmits the cross-level effects into instructional innovation. Teacher and school controls are included to reduce confounding.

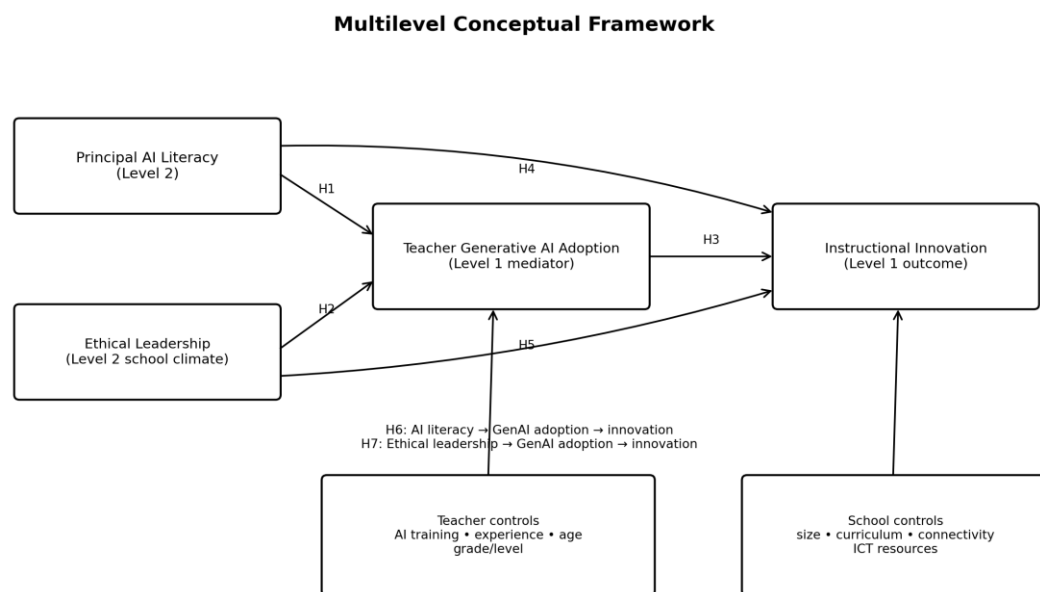


Figure 1. Conceptual framework for principal AI literacy, ethical leadership, teacher GenAI adoption and instructional innovation

Method

Design

The study will use a quantitative explanatory multilevel design with matched principal–teacher data. The design is appropriate because teachers are nested within schools and share the same principal, policies, infrastructure and organisational climate. Treating all teachers as statistically independent would underestimate standard errors and obscure whether variance in GenAI adoption and instructional innovation lies between schools as well as between teachers (Hox et al., 2017). The study therefore adopts a two-level structural equation modelling strategy capable of estimating direct cross-level effects and 2-1-1 mediation (Preacher et al., 2010).

To reduce common method bias and strengthen temporal ordering, data collection will be separated into two teacher waves. At Time 1, principals will complete the AI-literacy measure and school-profile questions, while teachers will rate the principal’s ethical leadership, report their current GenAI adoption and provide background information. Approximately four to six weeks later, the same teachers will complete the instructional-innovation measure. Anonymous school and teacher codes will link the waves without recording names. This design is stronger than a single-wave self-report survey because the principal predictor comes from a different source and the final outcome is temporally separated (Podsakoff et al., 2003).

The Study Context and Population

The study will be conducted in licensed Montessori and Montessori-oriented private pre-tertiary schools in Greater Accra, Ghana. NaSIA is the statutory body responsible for licensing and regulating pre-tertiary schools in Ghana, and its 2025 first-quarter report recorded 855 licensed private schools in Greater Accra, providing a broad institutional frame from which eligible schools can be identified (NaSIA, 2025). Because “Montessori” is used with different degrees of fidelity in the private-school sector, eligibility will be operationalised transparently: schools must be licensed, located in Greater Accra, provide at least kindergarten or basic-school education, and publicly identify Montessori or Montessori-oriented pedagogy as part of their instructional model. The study will not assume international Montessori accreditation unless independently verified.

The Level-2 population comprises principals or headteachers of eligible schools. The Level-1 population comprises classroom teachers employed in those same schools who have at least one academic term of service and who undertake lesson planning or classroom teaching.

Teachers who perform only administrative or non-instructional duties will be excluded because the dependent variable concerns instructional innovation. The nested population structure permits each principal's AI literacy and the shared ethical-leadership climate to be matched to multiple teacher outcomes within the same school.

Sampling

Sampling will proceed in multiple stages. First, a sampling frame of eligible licensed schools will be created from NaSIA records and verified through school websites or direct contact. Second, schools will be stratified by municipality and, where the frame permits, by school size or curriculum orientation to avoid over-concentration in one part of Greater Accra. Third, schools will be randomly selected within strata. One principal will be recruited from every participating school, and approximately eight to ten eligible teachers will then be randomly selected from the staff list of each school.

For multilevel SEM, statistical power depends more heavily on the number of Level-2 units than on adding large numbers of teachers within a small number of schools. The study will therefore target at least 60 schools, yielding approximately 60 principals and 480–600 teachers if eight to ten teachers participate per school. A minimum of 50 usable school clusters will be treated as the lower practical threshold, while the final target will be checked using Monte Carlo power analysis for the smallest theoretically important cross-level path before data collection (Hox et al., 2017; Preacher et al., 2010). If the verified number of eligible Montessori schools is below the target, the study will attempt a census of all eligible schools rather than reduce the cluster count through convenience sampling.

Instrument

A matched questionnaire system will be used. Principal AI literacy will be adapted from the 12-item Artificial Intelligence Literacy Scale developed by Wang et al. (2023), which measures awareness, usage, evaluation and ethics. Items will be contextualised for school leadership without altering the underlying dimensions. The principal form will also capture years of leadership experience, prior AI training, school enrolment, ICT-resource availability, internet reliability and curriculum orientation. A five-point response format will be used for latent constructs unless the source instrument specifies a frequency scale.

Teachers will complete three principal constructs. Ethical leadership will be measured with the 10-item Ethical Leadership Scale developed by Brown et al. (2005), worded to refer explicitly to the school principal. Teacher GenAI adoption will be measured as the breadth

and regularity with which teachers use GenAI for lesson planning, resource creation, differentiation, assessment design, feedback, professional learning and student-learning activities; items will be adapted from recent teacher GenAI integration research rather than measuring intention alone (Collie & Martin, 2024; Cheah et al., 2025). Instructional innovation will be measured using an education-adapted innovative work behaviour scale covering idea generation, idea promotion and idea implementation, drawing on Janssen (2000) and subsequent teacher validation studies (Kuril et al., 2023; Hosseini et al., 2021).

Table 1. Measurement Blueprint.

Construct	Source respondent	Items	Core dimensions	Primary source
Principal AI Literacy (PAIL)	Principal	12	Awareness; use; evaluation; ethics	Wang et al. (2023); UNESCO (2024)
Ethical Leadership (EL)	Teacher	10	Fairness; integrity; communication; ethical modelling	Brown et al. (2005)
GenAI Adoption (GA)	Teacher	6–8	Planning; materials; differentiation; assessment; feedback; learning activities	Collie & Martin (2024); Cheah et al. (2025)
Instructional Innovation (II)	Teacher	9	Idea generation; promotion; implementation	Janssen (2000); Kuril et al. (2023)

Pilot Study

The matched instruments will be piloted in Montessori-oriented schools outside the final school sample. The pilot should involve approximately 10–15 principals and 30–50 teachers, sufficient to assess wording, completion time, role clarity, matching procedures and preliminary internal consistency. Cognitive debriefing will be conducted with a small subset to determine whether teachers distinguish AI adoption from general educational technology use and whether principals understand AI-literacy items as competence rather than confidence. Items with ambiguous wording, double-barrelled content or contextually inappropriate examples will be revised before the main study (Wang et al., 2023; Arkorful et al., 2025).

Validity, Reliability and Common Method Bias

Measurement quality will be assessed before structural paths are interpreted. At the teacher level, confirmatory factor analysis will test ethical leadership, GenAI adoption and instructional innovation as distinct latent constructs. Indicator loadings of approximately .70

or higher will be preferred, while composite reliability and omega values above .70 and average variance extracted values above .50 will indicate adequate internal consistency and convergent validity. Discriminant validity will be evaluated through factor correlations and HTMT, and competing measurement models will be compared where constructs show strong overlap (Kline, 2023).

Because ethical leadership is intended to represent a shared school-level climate, aggregation will only occur if teacher ratings demonstrate sufficient within-school agreement and between-school reliability. ICC(1) will indicate the proportion of variance attributable to schools, ICC(2) will assess reliability of school means, and rwg(j) will be reported as an index of within-school agreement. If aggregation is weak, ethical leadership will be modelled as a latent between-school factor through multilevel CFA rather than forcing a school mean. This step is essential because a leadership construct should not be treated as Level 2 simply because the researcher intends it to be organisational (Hox et al., 2017).

The matched design reduces common method risk because principal AI literacy comes from principals and the instructional-innovation outcome is collected in a later teacher wave. Procedural remedies will also include confidentiality, psychologically separating predictor and outcome sections, neutral item wording and varying item order. Statistical diagnostics will examine a common latent method factor or marker-variable sensitivity model if the measurement structure permits, rather than relying solely on Harman's one-factor test (Podsakoff et al., 2003).

Data Collection Procedure

After ethics approval and institutional permission, eligible school leaders will receive an invitation explaining the matched design. Each participating school will be assigned a non-identifying school code. Principals will complete the AI-literacy questionnaire electronically or in sealed paper form. Selected teachers will receive a corresponding school code and unique teacher code. Time-1 teacher data will include ethical-leadership ratings, GenAI adoption and background characteristics. Time-2 data, collected four to six weeks later, will contain instructional-innovation items and the same anonymous teacher code. No student-level personal data will be collected.

Completed records will be screened for unmatched codes, duplicate entries, excessive missing data and response-pattern anomalies. Teacher responses will be retained only where the school has a valid principal record and sufficient teacher participation to estimate school-level ethical leadership. The researcher will maintain a separate encrypted linkage file

containing only anonymous codes and collection status; it will not contain participant names. The analysis dataset will therefore preserve the principal–teacher hierarchy without exposing individual identities.

Data Analysis

Data screening and descriptive analysis will be conducted in SPSS or R, while multilevel confirmatory factor analysis and structural modelling will be estimated in Mplus or an equivalent multilevel SEM environment. The analytical sequence deliberately follows the logic of the attached reference article—descriptive profile, correlations, measurement model, reliability and validity, collinearity/model fit, structural paths and predictive/explanatory statistics—but adapts each stage to nested data. This prevents the common error of applying single-level SEM to teachers clustered under the same principal (Hox et al., 2017; Preacher et al., 2010).

The first stage will describe principal and teacher characteristics, missingness and distributional properties. Means, standard deviations and zero-order correlations will be reported for all study constructs. Intraclass correlations for GenAI adoption and instructional innovation will quantify school-level clustering. The measurement stage will then estimate a two-level CFA to establish that the teacher-level constructs are empirically distinct and that between-school ethical leadership is reliable. Where necessary, robust maximum likelihood estimation will be used to accommodate non-normal item distributions (Kline, 2023).

The structural model will then test H1–H5 as direct paths and H6–H7 as cross-level indirect effects. The primary model is a 2-1-1 mediation structure: principal AI literacy and ethical leadership are Level-2 predictors; teacher GenAI adoption is a Level-1 mediator whose between-school component is predicted by Level-2 variables; and instructional innovation is a Level-1 outcome. Indirect effects will be estimated using Monte Carlo confidence intervals or equivalent multilevel indirect-effect procedures, which are appropriate for products of coefficients in multilevel mediation (Preacher et al., 2010).

Model evaluation will include chi-square, CFI, TLI, RMSEA and SRMR reported separately where available for within- and between-school components. Standardised coefficients, 95% confidence intervals and p values will be used for hypothesis decisions. R^2 will be reported for GenAI adoption and instructional innovation at relevant levels, and sensitivity analyses will control for teacher age, gender, teaching experience, prior AI training and grade level, as well as school size, connectivity and ICT resources. A second model will test whether

conclusions are robust when GenAI adoption is represented by breadth of pedagogical use rather than a single composite.

Measurement Model Specification

Principal AI literacy will be represented as a Level-2 composite or latent construct depending on the achieved school-level sample and item performance. Ethical leadership will be specified as a teacher-rated construct with a between-school component after aggregation or multilevel CFA verification. GenAI adoption and instructional innovation will be modelled as reflective teacher-level latent variables. The measurement model will therefore respect the source of each construct and avoid forcing principal self-reports and teacher perceptions into one undifferentiated covariance matrix.

Structural Model Specification

The primary Level-1 equations are specified as: $GA_{ij} = \pi_{0j} + \Sigma \pi_{qj}(\text{Control}_{qij}) + e_{1ij}$ and $II_{ij} = \beta_{0j} + \beta_1(GA_{ij}) + \Sigma \beta_{qj}(\text{Control}_{qij}) + e_{2ij}$, where teacher i is nested in school j . At Level 2, the school-specific intercept for GenAI adoption is modelled as $\pi_{0j} = \gamma_{00} + \gamma_{01}(\text{PAIL}_j) + \gamma_{02}(\text{EL}_j) + \gamma_{03}(\text{SchoolControls}_j) + u_{0j}$. Instructional innovation is modelled with $\beta_{0j} = \delta_{00} + \delta_{01}(\text{PAIL}_j) + \delta_{02}(\text{EL}_j) + \delta_{03}(\text{SchoolControls}_j) + v_{0j}$. The indirect effects are $\gamma_{01} \times \beta_1$ for principal AI literacy and $\gamma_{02} \times \beta_1$ for ethical leadership. This specification separates within-school teacher variation from between-school leadership effects and directly tests the proposed mediation.

Ethical Considerations

Ethical approval will be obtained before fieldwork. Participation will be voluntary, principals and teachers will provide informed consent, and refusal will have no employment consequence. Because teachers will rate their principals, recruitment and data handling will be designed to prevent principals from seeing individual responses. Reports will identify neither schools nor participants. AI-related questions will focus on professional practice rather than asking teachers to upload student information or disclose confidential prompts. Data will be stored securely, and any later public dataset will be de-identified at both school and teacher levels. These protections align with UNESCO's human-centred approach to AI in education and with the ethical risks specific to AI-mediated schooling (Miao & Holmes, 2023; Ho, 2026).

Results and Analysis Framework

The attached reference article reports a complete empirical sequence from respondent profile through structural paths, model fit and predictive accuracy. The same sequence should be used here after the matched dataset is collected, with additional multilevel diagnostics. Numerical values are deliberately left blank in this draft because no field dataset was supplied; inserting invented coefficients would convert a research design into fabricated evidence.

Respondent Profile

Table 2. Profile of Principals and Teachers.

Level	Variable	Category	Frequency	Percent
Principal	Sex	[n / %]	[n / %]	-
Principal	Leadership experience	[categories]	[n / %]	-
Principal	Prior AI training	Yes/No	[n / %]	-
Teacher	Sex	[n / %]	[n / %]	[n / %]
Teacher	Teaching experience	[categories]	[n / %]	-
Teacher	Grade/level taught	KG/Primary/JHS	[n / %]	-
Teacher	Prior GenAI training	Yes/No	[n / %]	-

Descriptive Statistics and Correlation

Table 3. Descriptive Statistics and Correlation Matrix.

Construct	M	SD	1	2	3	4
Principal AI Literacy	[M]	[SD]	1			
Ethical Leadership	[M]	[SD]	[r]	1		
GenAI Adoption	[M]	[SD]	[r]	[r]	1	
Instructional Innovation	[M]	[SD]	[r]	[r]	[r]	1

The narrative accompanying Table 3 should identify the strongest and weakest associations, note whether correlations are in the hypothesised direction, and avoid treating correlations as evidence of cross-level causal effects. Correlations involving school-level constructs should be calculated at the appropriate level or clearly identified as aggregated estimates.

Measurement Model Assessment

Table 4. Measurement Model Factor Loadings.

Construct	Indicators	Standardised loading range
Principal AI Literacy	PAIL1–PAIL12	[loading range]
Ethical Leadership	EL1–EL10	[loading range]
GenAI Adoption	GA1–GA8	[loading range]
Instructional Innovation	II1–II9	[loading range]

The results section should report whether indicators load as expected at the relevant level. Weak items should not be deleted solely to improve fit; deletion must be justified theoretically and checked for effects on content validity. The final paper should report any modifications transparently.

Construct Reliability and Validity

Table 5. Construct Reliability and Convergent Validity.

Variable	Alpha/Omega	CR	AVE
Principal AI Literacy	[α/ω]	[CR]	[AVE]
Ethical Leadership	[α/ω]	[CR]	[AVE]
GenAI Adoption	[α/ω]	[CR]	[AVE]
Instructional Innovation	[α/ω]	[CR]	[AVE]

Discriminant Validity

Table 6. HTMT Discriminant Validity Matrix.

Construct	PAIL	EL	GA	II
PAIL	–			
EL	[HTMT]	–		
GA	[HTMT]	[HTMT]	–	
II	[HTMT]	[HTMT]	[HTMT]	–

Multilevel Aggregation and Intraclass Correlation

Table 7. Multilevel Aggregation and Clustering Diagnostics.

Construct	ICC(1)	ICC(2)	rwg(j)	Decision
Ethical Leadership	[ICC(1)]	[ICC(2)]	[rwg(j)]	Aggregate / latent between factor
GenAI Adoption	[ICC(1)]	-	-	Confirms between-school variance
Instructional Innovation	[ICC(1)]	-	-	Confirms between-school variance

Model Fit

Table 8. Multilevel Model Fit Indices.

Fit index	Estimate	Reference interpretation
Chi-square	[value]	Sensitive to N
CFI	[value]	$\geq .90$ acceptable; $\geq .95$ strong
TLI	[value]	$\geq .90$ acceptable; $\geq .95$ strong
RMSEA	[value]	$\leq .08$ acceptable; $\leq .06$ strong
SRMR within	[value]	$\leq .08$ preferred
SRMR between	[value]	$\leq .08$ preferred

Structural Model Analysis

Table 9. Direct Structural Paths.

Hypothesis	Path	β	SE	p	95% CI	Decision
H1	PAIL $\rightarrow$ GA	$[\beta]$	$[SE]$	$[p]$	$[95\% CI]$	Supported/Not
H2	EL $\rightarrow$ GA	$[\beta]$	$[SE]$	$[p]$	$[95\% CI]$	Supported/Not
H3	GA $\rightarrow$ II	$[\beta]$	$[SE]$	$[p]$	$[95\% CI]$	Supported/Not
H4	PAIL $\rightarrow$ II	$[\beta]$	$[SE]$	$[p]$	$[95\% CI]$	Supported/Not
H5	EL $\rightarrow$ II	$[\beta]$	$[SE]$	$[p]$	$[95\% CI]$	Supported/Not

Mediation Analysis

Table 10. Cross-Level Indirect Effects.

Hypothesis	Indirect path	Effect	95% CI low	95% CI high	Decision
H6	PAIL $\rightarrow$ GA $\rightarrow$ II	$[\text{indirect } \beta]$	$[CI \text{ lower}]$	$[CI \text{ upper}]$	Supported/Not
H7	EL $\rightarrow$ GA $\rightarrow$ II	$[\text{indirect } \beta]$	$[CI \text{ lower}]$	$[CI \text{ upper}]$	Supported/Not

Coefficient of Determination and Explanatory Power

Table 11. Coefficient of Determination.

Outcome	R ²	Interpretation
GenAI Adoption – between schools	$[R^2]$	Variance in school-level adoption explained by PAIL, EL and controls
Instructional Innovation – within schools	$[R^2]$	Teacher-level variation explained by adoption and controls
Instructional Innovation – between schools	$[R^2]$	School-level variation explained by leadership and adoption

DISCUSSION FRAMEWORK

The final Discussion should follow the same hypothesis-by-hypothesis logic used in the reference article. It should begin with the effect of principal AI literacy on teacher GenAI adoption, then ethical leadership on adoption, adoption on instructional innovation, the two direct leadership–innovation paths and finally the two indirect effects. Each paragraph should state whether the hypothesis was supported, interpret the mechanism, compare the result with prior evidence and explain why the Montessori/Ghanaian context may strengthen or qualify the relationship. The discussion should not repeat coefficients without interpretation.

If H1 is supported, the result would extend teacher-focused AI-literacy research by showing that AI competence at the leadership level has cross-level consequences for adoption. Such a finding would complement Ghanaian evidence on teachers' own AI literacy by demonstrating that the school's technological leadership capacity matters beyond individual teacher knowledge (Arkorful et al., 2025; Arkorful et al., 2026). If H1 is not supported, the

discussion should consider whether teacher autonomy, peer learning or access to external AI information makes principal competence less influential than expected.

If H2 is supported, the result would position ethical leadership as an enabling condition for responsible GenAI adoption rather than merely a predictor of traditional organisational attitudes. This would be consistent with evidence that ethical school leadership builds trust, justice and teacher motivation and with emerging arguments that ethical leadership is essential for digital pedagogical agency (Özdoğan & Sarier, 2024; Mphatsoane-Sesoane & Jita, 2025). If the effect is weak, it may indicate that ethical leadership shapes how AI is used more than whether it is used.

Support for H3 would show that adoption becomes educationally consequential when it is connected to the generation and implementation of new instructional practices. This would move beyond research that measures GenAI intention or preparedness as end points and instead examine whether use produces pedagogical change (Cheah et al., 2025; Collie & Martin, 2024). In Montessori settings, the interpretation should distinguish teacher-supportive innovation from uses that displace learner agency or hands-on activity.

The mediation hypotheses are theoretically central. Significant indirect effects would show that principal competence and ethical conduct create innovation partly by changing teacher behaviour, not merely through direct leader influence. This would extend UTAUT by locating school leadership as a Level-2 source of facilitating conditions and social influence, while extending Social Learning Theory by showing that leader modelling translates into a specific technology-use mechanism. Non-significant mediation would suggest that other mechanisms—such as AI self-efficacy, professional learning, psychological safety or school digital infrastructure—should be tested in future models (Venkatesh et al., 2003; Brown et al., 2005; Hazzan-Bishara et al., 2025).

Theoretical Implications

The study is designed to make four theoretical contributions. First, it extends technology-adoption theory from the individual teacher to the multilevel school context. UTAUT is commonly applied to individual acceptance, but the proposed model treats principal AI literacy and ethical leadership as school-level antecedents that shape shared facilitating conditions and social influence. This helps explain why teachers with similar personal backgrounds may adopt GenAI differently when they work under different principals (Venkatesh et al., 2003; Collie & Martin, 2024).

Second, the model extends Social Learning Theory into AI-enabled educational leadership by testing technological competence and ethical modelling together. Existing ethical-leadership research shows that leaders influence trust, fairness and commitment, while emerging AI-leadership work highlights privacy, bias, autonomy and accountability (Özdoğru & Sarier, 2024; Ho, 2026). The proposed model asks whether these ethical signals have observable cross-level effects on technology use and pedagogical innovation.

Third, the study theorises GenAI adoption as a mediating mechanism rather than an endpoint. Many educational AI studies stop at intention, acceptance or readiness. By modelling instructional innovation downstream from adoption, the study distinguishes technology use from educational value. This responds to UNESCO's emphasis on AI-enhanced pedagogical innovation and human agency rather than adoption for its own sake (Miao & Cukurova, 2024).

Fourth, the study introduces matched principal–teacher multilevel evidence from Ghana into a literature dominated by teacher-only, single-level and Global North studies. The design therefore contributes methodologically as well as contextually. It also responds to cross-sector evidence that leadership conditions determine whether AI capability produces valued outcomes, while examining that proposition in a pedagogically distinctive school environment (Marfo et al., 2026; Arkorful et al., 2026).

Practical, Policy and Managerial Implications

The practical implication is that schools should not treat AI transformation as a software-purchasing exercise. Principal professional development should combine technical AI literacy with pedagogical judgement and ethical governance. A principal who can operate AI tools but cannot evaluate bias, privacy, reliability or age appropriateness may encourage unsafe adoption; a principal who is ethically careful but technologically uninformed may respond with blanket restriction. Leadership development should therefore integrate both competencies (Miao & Cukurova, 2024; Ho, 2026).

For Montessori and Montessori-oriented schools, AI policy should define which uses complement rather than displace the pedagogy. GenAI may be suitable for teacher planning, differentiated resources, language adaptation, formative questioning and professional reflection, while direct learner-facing use should be age-appropriate and should not weaken hands-on exploration, social interaction or independent reasoning. School-level AI governance should specify human review, data protection, permitted tools, copyright

expectations and procedures for reporting errors or harmful outputs (Miao & Holmes, 2023; Lillard, 2017).

At policy level, NaSIA, teacher-licensing bodies, school associations and professional-development providers can use the findings to design leadership standards for AI-enabled schools. Ghanaian evidence already shows that teacher AI literacy is uneven; leadership-focused capacity building would address a complementary gap by preparing principals to create trustworthy enabling environments for teacher adoption (Arkorful et al., 2025; Arkorful et al., 2026). Rather than mandate identical technology use across schools, policy should establish ethical minimum standards while allowing pedagogical adaptation to school context.

Limitations and Future Research

Several limitations should be anticipated. First, the design remains nonexperimental, so even two-wave mediation cannot establish causality as strongly as a longitudinal panel or intervention. Future studies could train principals in AI literacy and ethical AI leadership and compare teacher adoption trajectories over time. Second, the study focuses on private Montessori and Montessori-oriented schools in Greater Accra, which may limit generalisability to public schools, rural settings or schools using different pedagogies. Comparative research should test whether the multilevel relationships are invariant across school sectors and regions.

Third, teacher GenAI adoption and instructional innovation rely partly on self-report and may be affected by social desirability. Future research could incorporate lesson artefacts, anonymised AI-use logs, peer observation or instructional portfolios. Fourth, principal AI literacy is measured from principals themselves; adding a performance-based AI-literacy task would reduce confidence bias. Finally, the proposed model does not include teacher AI self-efficacy, professional learning climate or digital infrastructure as mediators. These variables may explain additional pathways between leadership and classroom innovation (Hazzan-Bishara et al., 2025; Cheah et al., 2025).

CONCLUSION

This study proposes that the AI-enabled school is not created by access to generative AI alone. It is created when school leaders possess enough AI literacy to make informed technological and pedagogical decisions and enough ethical leadership capacity to establish trust, fairness, accountability and clear boundaries for experimentation. The multilevel model

links these school-level capabilities to teachers' GenAI adoption and, through adoption, to instructional innovation. By using matched principal–teacher data and multilevel SEM, the study is positioned to test whether differences between schools are partly leadership differences rather than merely differences between individual teachers.

The model is particularly relevant to Montessori and Montessori-oriented schools in Greater Accra because innovation must be balanced with learner autonomy, developmental appropriateness and human-centred pedagogy. If the hypotheses are supported, the practical message will be clear: schools seeking meaningful returns from GenAI should develop principals as both technologically literate and ethically credible leaders. If some paths are unsupported, the multilevel design will still identify where leadership influence stops and where teacher- or infrastructure-level explanations become more important. Either outcome advances understanding of how schools can move from AI availability to responsible instructional innovation.

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