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HUMAN-AGENT COLLABORATION IN SMART-CLASSROOMS: EVALUATING THE EFFECTIVENCESS OF AGENTIC AI AS A VIRTUAL TEACHING ASSISTANT

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Abstract

The rapid advancement of AI has introduced Agentic AI, which encompasses autonomous intelligent systems that engage in reasoning, planning, decision-making, and collaboration with humans. Unlike traditional generative AI, which responds to prompts, Agentic AI acts as an intelligent collaborator that enhances instructional delivery and student learning. Although the deployment of AI in education is increasing, there is limited empirical research regarding the efficacy of Agentic AI as a Virtual Teaching Assistant (VTA) in boosting human-agent collaboration in smart classrooms. Most existing studies focus on

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reactive AI, neglecting the autonomous features of Agentic AI and their influence on educational outcomes. This study seeks to assess the role of Agentic AI as a VTA in promoting human-agent collaboration, student engagement, and learning results within smart classroom settings. A quantitative research design, employing cross-sectional surveys, will gather data from university lecturers and students, analyzed through Structural Equation Modelling (SEM). The research is anticipated to reveal that Agentic AI enhances classroom interactions, personalized learning, instructional efficiency, and overall student engagement, leading to improved academic performance. Furthermore, the study aims to provide practical recommendations for higher education institutions aiming to incorporate autonomous AI into their educational practices. A key contribution of this work is the development of the Human-Agent Collaborative Smart Classroom (HACSC) Framework, which melds Human-AI Collaboration Theory, the Technology Acceptance Model (TAM), and Activity Theory to elucidate how Agentic AI can innovate smart classroom pedagogy and educational practices.

Keywords: Agentic AI, Human-Agent Collaboration, Smart Classrooms, Virtual Teaching Assistant, Student Engagement, Learning Outcomes, Educational Technology.

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1. Introduction

Artificial Intelligence (AI) has transformed education through automation, adaptive learning, and personalised support. Its integration with the Internet of Things (IoT) has enabled smart classrooms that support real-time monitoring and data-informed teaching. Although generative AI tools such as ChatGPT and Google Gemini assist with academic tasks, they are largely reactive and have limited proactive decision-making and long-term memory (Gonzalez et al., 2026; Johri et al., 2026). Agentic AI introduces autonomous reasoning, planning, contextual memory, and adaptive decision-making, creating opportunities for more effective Virtual Teaching Assistants (VTAs) and Human–Agent Collaboration (Varsha et al., 2021). However, evidence concerning its effects on student engagement, academic performance, and classroom management remains limited (Almirall, 2026). This study evaluates Agentic AI as a VTA in higher education smart classrooms. It examines its influence on classroom interaction, student engagement,

teaching efficiency, and learning outcomes, while investigating lecturers' acceptance, trust, ease of use, and institutional support. The study also considers ethical issues, including privacy, governance, and accountability. Drawing on Human–AI Collaboration Theory and the Technology Acceptance Model (TAM), it proposes the HACSC Framework to guide collaboration among lecturers, students, and AI systems. Practically, the study aims to support institutional decisions on Agentic AI adoption. The HACSC Framework guides integrating AI into academic support services, while the proposed policy recommendations and implementation roadmap address ethical governance, infrastructure, and faculty development.

2. Literature Review

This section provides the literature review explored in this research.

AI in Education (AIED)

Artificial Intelligence in Education (AIED) combines computer science, educational psychology, and instructional technology to improve teaching and learning. Its development progressed from early expert systems to Intelligent Tutoring Systems (ITS), adaptive learning platforms, educational chatbots, learning analytics, and virtual tutors. These technologies support personalised instruction, student monitoring, and academic assistance, but concerns remain regarding data privacy, algorithmic bias, and limited proactive engagement (Becker et al., 2026; Villa et al., 2021). Most existing systems remain reactive and lack autonomous decision-making capabilities (Li, 2025). Agentic AI therefore presents an emerging research opportunity by introducing autonomous reasoning, proactive support, and human–AI collaboration. Investigating its effectiveness could help advance AIED towards more adaptive and collaborative educational environments (Xu et al., 2026).

Smart Classroom Technologies

Digital transformation has encouraged the adoption of smart classrooms in higher education, combining AI, the IoT, cloud computing, learning analytics, and intelligent automation to support interactive and learner-centred education (Cui et al., 2026). These technologies aim to improve teaching effectiveness, personalise learning, increase student engagement, and support evidence-based decisions within the Education 4.0 framework. IoT-enabled devices, including smart boards, RFID attendance systems, and sensors, facilitate classroom monitoring and management through real-time data on attendance, occupancy, and environmental conditions (Zeng et al., 2026). Learning analytics further supports performance monitoring and personalised interventions, although effective implementation requires attention to data governance and privacy (Olujimi et al., 2026), as shown in Figure 1



Figure 1. An Overview of Smart Classroom Technologies

Augmented Reality (AR), Virtual Reality (VR), Digital Twins, and Edge Computing enhance smart classrooms through immersive learning, virtual environment modelling, efficient resource management, and faster data processing (Almirall, 2026). However, limited integration of autonomous AI agents restricts the development of fully intelligent classroom ecosystems. Agentic AI could address this gap by coordinating

these technologies and enabling proactive educational support, although research on such integration remains limited.

Agentic AI

Agentic AI extends traditional and generative AI through autonomous reasoning, goal-oriented planning, adaptive decision-making, and collaborative problem-solving. Unlike systems that depend on predefined instructions, it can perceive situations, plan actions, perform tasks, and learn from outcomes with limited human intervention (Johri et al., 2026). Key features include autonomy, reasoning, planning, memory, self-reflection, collaboration, and goal decomposition (Ajmal et al., 2025). Its architecture commonly combines planners, executors, memory, tool use, and reflection. These capabilities make Agentic AI relevant to smart classrooms by supporting proactive educational assistance and collaboration between lecturers and intelligent systems (Johri et al., 2026).

Table 2.1. Comparison between Generative AI and Agentic AI

Feature	Generative AI	Agentic AI
Primary purpose	Generates content in response to prompts	Achieves goals through autonomous planning and execution
User interaction	Reactive: waits for user prompts	Proactive: initiates actions when appropriate
Decision-making	Limited to immediate prompt interpretation	Autonomous, context-aware, and goal-driven
Autonomy	Low	High
Planning capability	Minimal or absent	Advanced multi-step planning
Reasoning	Generates plausible responses based on learned patterns	Performs contextual reasoning and decision-making
Memory	Mostly short-term conversational context	Persistent short-term and long-term memory
Goal management	Single prompt at a time	Decomposes complex goals into multiple tasks
Collaboration	Acts primarily as an assistant	Functions as an intelligent collaborator and teammate
Tool integration	Limited or user-directed	Dynamically selects and uses multiple tools autonomously
Self-reflection	Limited	Continuously evaluates and improves performance
Educational role	Answers questions, generates learning materials, and supports writing	Monitors learning, personalizes instruction, coordinates classroom activities, and collaborates with lecturers
Typical examples	ChatGPT, Gemini, Claude, Microsoft Copilot	Autonomous AI teaching assistants, multi-agent educational systems, and AI orchestration platforms

Agentic AI in higher education is still emerging, with most applications centred on generative AI, tutoring, and chatbots. Limited empirical research has examined autonomous AI agents as instructional partners, particularly their effects on lecturer–AI collaboration, student

engagement, instructional quality, trust, governance, and learning outcomes (Pashkevich et al., 2023). Further research is therefore needed to support responsible and evidence-based use of agentic AI in higher education.

Human-Agent Collaboration

Human-Agent Collaboration focuses on combining human expertise with autonomous AI rather than replacing human roles. As AI develops from passive tools into autonomous agents, research increasingly examines how humans and AI can jointly solve problems and make decisions (Galster et al., 2025). In education, AI can support teaching and learning while educators retain responsibility for pedagogy and ethical decisions. This collaboration combines human strengths such as creativity and emotional intelligence with AI capabilities in data processing and prediction (Al-sharafi et al., 2026). Human-in-the-Loop (HITL) systems maintain human oversight, while AI teammates, mixed-initiative systems, and collaborative intelligence support shared decision-making. Human–AI Teaming Theory, Joint Cognitive Systems Theory, and Distributed Cognition Theory further explain how humans and AI can coordinate, adapt, and contribute to knowledge creation in smart classrooms, as illustrated in Figure 2.

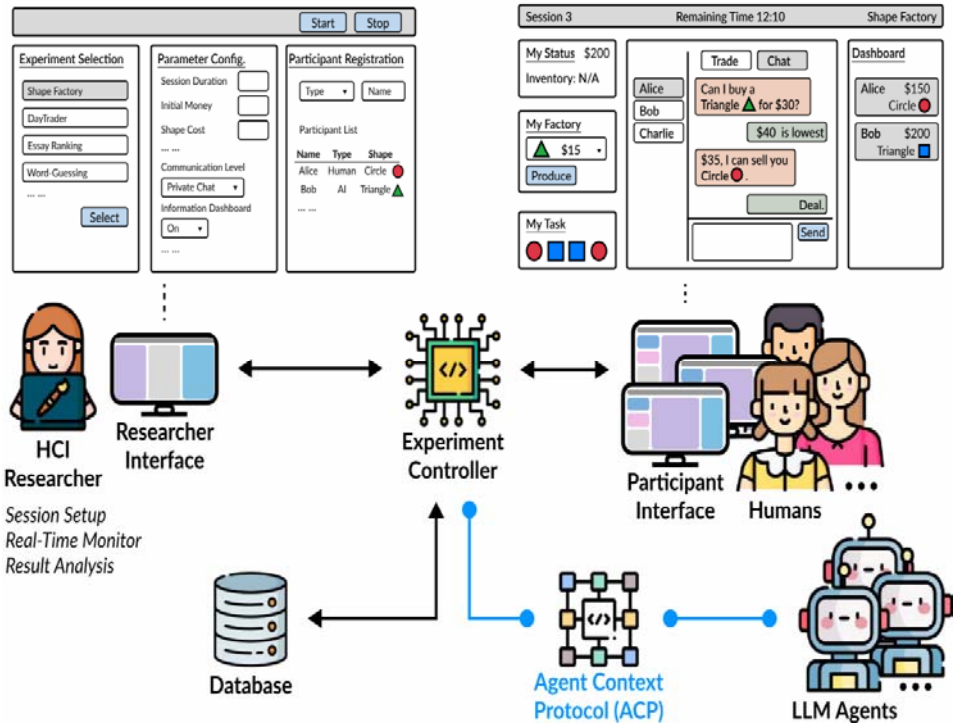


Figure 2: Human-Agent Collaboration

Although interest in Human–Agent Collaboration is increasing, research has largely examined reactive AI, with limited evidence on proactive collaboration in smart classrooms. Further research is needed to understand how AI can work effectively with educators and students to improve educational outcomes (Nallakaruppan et al., 2024). This study therefore proposes the HACSC Framework to examine these collaborative dynamics.

Virtual Teaching Assistants

Virtual Teaching Assistants (VTAs) are an important application of AI in Education, supporting teaching, learning, and student engagement in higher education. They automate routine activities, provide personalised assistance, and improve communication through

technologies such as natural language processing and machine learning (Naz et al., 2022). Unlike conventional learning management systems, VTAs can interact directly with students and support activities such as tutoring, assignments, attendance, assessment, academic discussions, and course recommendations (Zeng et al., 2026). Despite these benefits, most VTAs remain reactive and have limited ability to initiate interventions or independently adapt to changing learning needs. This creates a research gap for Agentic AI-powered VTAs that can act more proactively. The proposed HACSC Framework addresses this gap by examining how agentic VTAs can support more effective human–AI collaboration in smart classrooms.

Student Engagement

Student engagement is an important factor in academic success and includes students' attention, motivation, participation, and commitment to learning. It is commonly viewed as a multidimensional construct involving behavioural, emotional, cognitive, and social dimensions. Agentic AI can potentially support these dimensions through personalised feedback, monitoring of learning activities, and facilitation of collaboration. However, existing educational technologies often emphasise observable participation while giving less attention to emotional, cognitive, and social engagement. Research on the ability of Agentic AI to address these dimensions remains limited. The proposed HACSC Framework therefore considers student engagement as an important link between Human–Agent Collaboration and improved educational outcomes.

Learning Outcomes

Learning outcomes indicate the knowledge, skills, and competencies students gain from a course or programme and are important measures of teaching and educational effectiveness. Although traditionally

assessed through grades and examinations, learning outcomes now extend beyond academic scores (Gad, 2022). This study assesses learning outcomes using five indicators: GPA, knowledge retention, critical thinking, student satisfaction, and completion rate. GPA reflects academic performance, while knowledge retention measures students' ability to remember and apply learning. Critical thinking assesses reasoning and problem-solving, student satisfaction reflects perceptions of educational experiences, and completion rate indicates successful course completion. Agentic AI may support these outcomes through personalised tutoring, adaptive feedback, and continuous learning assistance (Maghrabi et al., 2024). It may also support critical thinking, satisfaction, and completion by encouraging problem-solving, providing timely feedback, and identifying students who require additional support (Sufi, 2022). However, limited research has examined the combined influence of Agentic AI on these multidimensional learning outcomes. The HACSC Framework therefore examines this relationship and the educational value of Agentic AI as a Virtual Teaching Assistant.

Technology Acceptance

Successful AI adoption in higher education depends not only on technological capability but also on users' willingness to adopt and use AI. Factors such as perceived usefulness, ease of use, trust, and social influence can influence technology acceptance. The Technology Acceptance Model (TAM) explains adoption through perceived usefulness and ease of use, while the Unified Theory of Acceptance and Use of Technology (UTAUT) highlights the role of organisational and social factors (Elkael et al., 2026). The Task–Technology Fit (TTF) model further emphasises the alignment between technology capabilities and users' tasks, while Human–AI Trust models highlight transparency, reliability, and ethical behaviour as important for effective collaboration.

Despite these models, limited research has examined acceptance of Agentic AI capable of autonomous reasoning and proactive decision-making (Zollo et al., 2021). The proposed HACSC Framework integrates TAM, UTAUT, TTF, and Human–AI Trust to examine technology acceptance of AI-powered Virtual Teaching Assistants in higher education.

Table 2. Comparison of Technology Acceptance Models

Model	Key Constructs	Strengths	Limitations	Relevance to Agentic AI
Technology Acceptance Model	Perceived Usefulness, Perceived Ease of Use	Simple, widely validated, and easy to apply	Ignores organizational and social factors	Explains lecturers' and students' willingness to use Agentic AI
UTAUT	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions	Comprehensive, incorporates organizational context	More complex; requires multiple variables	Explains institutional adoption of Agentic AI in universities
Task–Technology Fit (TTF)	Match between technology capabilities and user tasks	Focuses on performance improvement	Less emphasis on user attitudes	Evaluates whether Agentic AI supports teaching and learning tasks effectively
Human–AI Trust Model	Trust, transparency, explainability, reliability, accountability	Addresses collaboration with autonomous AI	Still evolving; limited empirical validation	Explains trust and sustained collaboration between lecturers and Agentic AI

Research on AI in Education has advanced through intelligent tutoring systems, chatbots, and adaptive learning platforms. However, limited attention has been given to Agentic AI as Virtual Teaching Assistants in smart classrooms. Existing systems are largely reactive, while integration with smart classroom environments remains limited (Ajmal et al., 2025). This study addresses these gaps by examining Agentic AI, Human–Agent Collaboration, student engagement, and learning outcomes through a proposed Human–Agent Collaborative Smart Classroom (HACSC) Framework.

3. Theoretical Framework

This study integrates the Technology Acceptance Model (TAM), Human–AI Teaming Theory, Joint Cognitive Systems (JCS) Theory, and Distributed Cognition Theory to explain the role of Agentic AI as a Virtual Teaching Assistant (VTA) in smart classrooms. TAM focuses on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as factors influencing users' acceptance of Agentic AI. Human–AI Teaming Theory complements TAM by viewing AI as a collaborative partner that can support teaching and student engagement (Jiang et al., 2026). JCS Theory views humans and AI as an integrated cognitive system involving shared decision-making and mutual adaptation, while Distributed Cognition Theory emphasises how knowledge emerges through interactions among people, technologies, and other learning resources. Together, these perspectives provide a broader understanding of Human–Agent Collaboration in smart classrooms (Liu et al., 2021). Human–AI Collaboration Theory further explains how humans and AI can combine complementary capabilities to achieve shared goals. In higher education, educators contribute contextual, creative, pedagogical, and ethical judgement, while AI supports data processing and personalised learning. Shared intelligence, Human-in-the-Loop (HITL), and trust are therefore important to effective collaboration (Olan et al., 2022). The framework proposes that these interactions can strengthen technology acceptance, collaboration, student engagement, and learning outcomes (Nwanji et al., 2020), as illustrated in Figure 3.

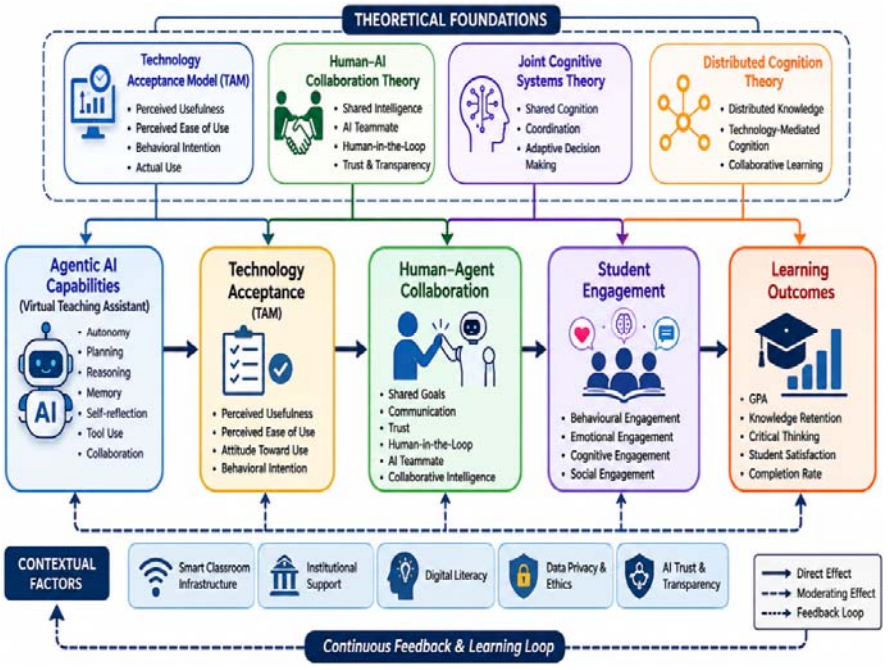


Figure 3. The Proposed Integrated Theoretical Framework

4. Conceptual Framework

The conceptual framework integrates the Technology Acceptance Model (TAM) and Human–AI Collaboration Theory to examine how Agentic AI influences educational outcomes in smart classrooms. It proposes that AI capabilities, including autonomy, planning, reasoning, and collaboration, affect Technology Acceptance and Human–Agent Collaboration, which subsequently influence Student Engagement and Learning Outcomes (Kabanda, 2026). Agentic AI represents the independent variable, while Technology Acceptance and Human–Agent Collaboration serve as mediating constructs. Technology Acceptance comprises Perceived Usefulness and Perceived Ease of Use, whereas Human–Agent Collaboration emphasises trust, shared intelligence, and joint decision-making. Student Engagement covers behavioural, emotional, cognitive, and social dimensions, while Learning Outcomes are assessed through indicators such as GPA and student satisfaction. The framework proposes that engagement improves learning outcomes

and that the relationships among these constructs can be tested using Structural Equation Modeling (SEM) (Yılmazdog˘an et al., 2021), as illustrated in Figure 4.

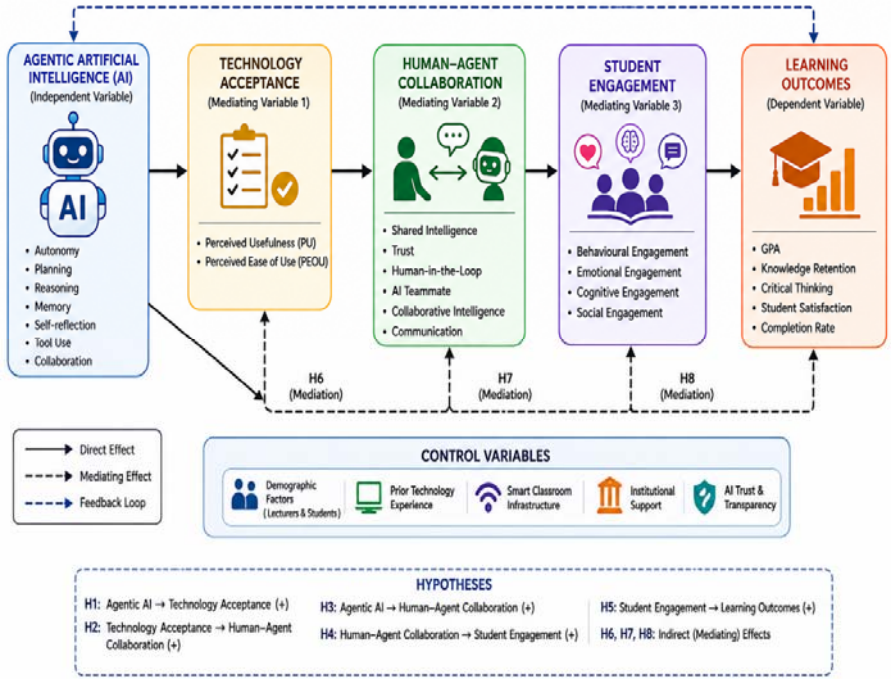


Figure 4. The Proposed Integrated Theoretical Framework

5. Methodology

This study adopts a positivist philosophy and a quantitative, cross-sectional survey design to evaluate Agentic AI as a Virtual Teaching Assistant and its contribution to Human–Agent Collaboration, technology acceptance, student engagement, and learning outcomes. The proposed sample comprises 300–600 lecturers, undergraduate and postgraduate students, and educational technology administrators selected through stratified random sampling. Proportional allocation and random selection will support group representation and reduce sampling bias. The data will be analysed using PLS-SEM, with a significance level of $p < 0.05$ and statistical power of at least 0.80. A 5-point Likert-scale questionnaire will assess Agentic AI capabilities, including autonomy,

reasoning, planning, memory, self-reflection, tool use, and collaboration. It will also measure perceived usefulness, perceived ease of use, trust, perceived autonomy, engagement, satisfaction, and behavioural intention. Expert review and pilot testing will be conducted to assess instrument reliability and validity. To address common method bias, the study will use counterbalanced item ordering, neutral wording, and confidentiality assurances. Following data collection, Harman's single-factor test and full collinearity assessment using VIF will be applied. As the study is proposed rather than completed, subsequent sections will present planned analyses and anticipated outcomes instead of empirical findings.

6. Proposed Human-Agent Collaboration Framework

The proposed Human–Agent Collaboration Framework (HACF) integrates Agentic AI as a collaborative Virtual Teaching Assistant (VTA) in smart classrooms. It positions AI as an autonomous partner that supports proactive reasoning, adaptive planning, and continuous collaboration with lecturers and students.

The framework consists of six layers:

1. *Agentic AI Capability Layer:* Includes autonomy, reasoning, planning, memory, self-reflection, tool use, and collaboration.
2. *Technology Acceptance Layer:* Incorporates TAM-related factors, including trust and explainability, to assess users' willingness to adopt Agentic AI.
3. *Human–Agent Collaboration Layer:* Promotes joint planning and evaluation by lecturers and AI, supported by ethical and pedagogical oversight.
4. *Collaborative Teaching Processes:* Assigns routine instructional tasks to AI while lecturers provide emotional support and retain final decision-making authority.
5. *Student Engagement:* Targets behavioural, emotional, cognitive, and social engagement.

6. *Learning Outcomes:* Seeks to improve academic performance and learner satisfaction.

HACF also incorporates feedback loops, adaptive learning, institutional governance, and ethical oversight to support responsible AI integration and balanced collaboration between educators and autonomous systems, as shown in Figure 5.

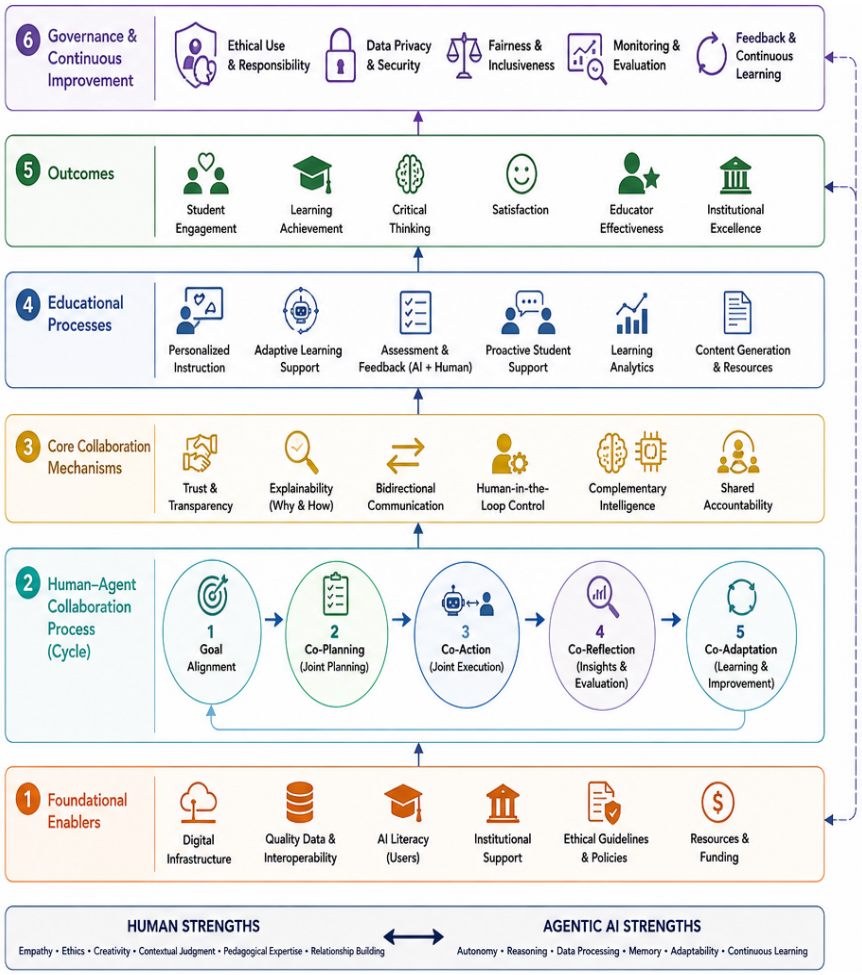


Figure 5. Proposed HACSC Framework

7. Proposed Data Analysis and Expected Results

Planned Respondent Demography

The study will assess whether Agentic AI-supported Virtual Teaching Assistants improve Human–Agent Collaboration, student engagement, and perceived learning outcomes. These relationships will be examined through quantitative analysis and interpreted using statistical evidence collected from university lecturers, students, and smart classroom users

Table 3. Respondent Profile

Variable	Categories	Statistical Analysis
Gender	Male, Female	Frequency, Percentage
Age	<20, 21–30, 31–40, 41–50, >50	Frequency, Percentage
Educational Level	Undergraduate, Postgraduate, Lecturer	Frequency, Percentage
Faculty/Department	Various Faculties	Frequency, Percentage
Teaching/Learning Experience	<2 years, 2–5 years, >5 years	Frequency, Percentage
Experience with AI	Beginner, Intermediate, Advanced	Frequency, Percentage
Smart Classroom Usage	Daily, Weekly, Occasionally	Frequency, Percentage

Measurement Model

The measurement model evaluates whether the questionnaire reliably and validly measures the latent constructs. It assesses internal consistency, convergent validity, and discriminant validity before testing the structural relationships.

Table 4. Measurement Model Evaluation

Assessment	Threshold	Interpretation
Factor Loading	≥ 0.70	Indicator reliability
Cronbach's Alpha	≥ 0.70	Internal consistency
Composite Reliability (CR)	≥ 0.70	Construct reliability
Average Variance Extracted (AVE)	≥ 0.50	Convergent validity
HTMT Ratio	< 0.85 (or 0.90)	Discriminant validity
Fornell-Larcker Criterion	Square root of AVE > Correlations	Discriminant validity

3. Structural Model

The structural model evaluates the proposed relationships among Agentic AI, Technology Acceptance, Human-Agent Collaboration, Student Engagement, and Learning Outcomes. The strength and significance of these relationships will be assessed after data collection using the specified SEM procedures.

Table 5. Structural Model Assessment

Assessment	Purpose
Path Coefficient (β)	Strength of relationship
t-value	Statistical significance
p-value	Hypothesis significance
R^2	Variance explained
Effect Size (f^2)	Contribution of the predictor
Predictive Relevance (Q^2)	Predictive capability

Hypothesis Testing

Hypothesis testing will determine whether the proposed relationships between constructs are statistically supported using bootstrapping analysis.

Table 6. Hypothesis Testing

Hypothesis	Relationship	Expected Direction
H1	Agentic AI → Technology Acceptance	Positive
H2	Technology Acceptance → Human–Agent Collaboration	Positive
H3	Agentic AI → Human–Agent Collaboration	Positive
H4	Human–Agent Collaboration → Student Engagement	Positive
H5	Student Engagement → Learning Outcomes	Positive

5. Indirect Effects (Mediation Analysis)

Mediation analysis determines whether one variable explains the relationship between two other variables. Bootstrapping is used to assess the significance of indirect effects.

Table 7. Mediation Analysis

Hypothesis	Mediator	Relationship
H6	Technology Acceptance	Agentic AI → Human–Agent Collaboration
H7	Human-Agent Collaboration	Agentic AI → Learning Outcomes
H8	Student Engagement	Human–Agent Collaboration → Learning Outcomes

Moderation Analysis

Moderation analysis examines whether external factors strengthen or weaken the relationships among the study variables. Variables such as AI Trust, Digital Literacy, or Smart Classroom Infrastructure may act as moderators.

Table 8. Moderating Variables

Moderator	Moderates Relationship
AI Trust	Agentic AI → Human–Agent Collaboration
Digital Literacy	Technology Acceptance → Human–Agent Collaboration
Smart Classroom Infrastructure	Human–Agent Collaboration → Student Engagement
Institutional Support	Technology Acceptance → Learning Outcomes
Prior AI Experience	Agentic AI → Technology Acceptance

Importance-Performance Map Analysis (IPMA)

Importance-Performance Map Analysis (IPMA) extends the PLS-SEM results by identifying which constructs have the greatest importance for improving Learning Outcomes while assessing their current performance. It helps prioritize managerial interventions.

Table 9. Importance-Performance Analysis

Construct	Importance	Performance	Recommended Action
Agentic AI Capabilities	High	Medium	Improve autonomy and reasoning
Technology Acceptance	High	High	Maintain current level
Human-Agent Collaboration	Very High	Medium	Enhance collaboration mechanisms
Student Engagement	Very High	Medium	Increase personalized learning
Learning Outcomes	Target Variable	—	Continuous improvement

Model Fit

Model fit evaluates how well the proposed conceptual framework represents the observed data. Good model fit indicates that the hypothesized model adequately explains the relationships among the variables.

Table 10. Model Fit Indices

Fit Index	Recommended Value	Interpretation
SRMR	< 0.08	Good fit
NFI	> 0.90	Acceptable fit
RMS Theta	< 0.12	Good fit (PLS-SEM)
Chi-square/df	< 3.00	Good fit
CFI	> 0.90	Good fit
TLI	> 0.90	Good fit
RMSEA	< 0.08	Good fit

Predictive Power

Predictive power assesses how well the proposed model predicts future observations. It evaluates the explanatory and predictive capability of the structural model using several statistical indicators.

Table 11. Predictive Power Assessment

Statistic	Threshold	Interpretation
R^2 = 0.75	Substantial	High explanatory power
R^2 = 0.50	Moderate	Moderate explanatory power
R^2 = 0.25	Weak	Low explanatory power
Q^2 > 0	Predictive relevance	Model predicts well
PLSpredict	Lower prediction error	Strong out-of-sample prediction
RMSE/MAE	Smaller values	Better predictive accuracy

These analyses will collectively provide a comprehensive evaluation of the proposed conceptual model, ensuring that the measurement instruments are reliable and valid, the hypothesized relationships are statistically supported, the mediating and moderating mechanisms are understood, and the model demonstrates both good fit and strong predictive capability. Such a framework is appropriate for empirical testing using SmartPLS 4.

8. Discussion

The discussion chapter interprets the empirical findings in relation to the research objectives, hypotheses, theoretical framework, and existing literature. It explains how the results contribute to understanding the role of Agentic AI as a VTA in fostering Human–Agent Collaboration, enhancing student engagement, and improving learning outcomes in smart classroom environments.

The study further proposes that effective Human–Agent Collaboration may be positively associated with student engagement and learning outcomes, particularly where Agentic AI VTAs complement rather than replace human lecturer involvement. However, the magnitude and statistical significance of these relationships cannot be

established until the proposed empirical data are collected and analyzed. The manuscript currently discusses moderate trust among some lecturers in this subsection.

Interpretation of Findings

The study examines the relationship between Agentic AI-supported Virtual Teaching Assistants (VTAs) and Human–Agent Collaboration in smart classrooms. It focuses on Agentic AI capabilities such as autonomous planning, proactive support, adaptive decision-making, and collaborative problem-solving, and tests their relationship with collaboration among lecturers, students, and AI. The study also examines whether Technology Acceptance influences Human–Agent Collaboration. Users who perceive Agentic AI as useful and easy to use may be more willing to integrate it into educational activities. This relationship will be empirically tested. In addition, the study investigates the relationship between Human–Agent Collaboration and Student Engagement, considering behavioural, emotional, cognitive, and social dimensions. It further examines whether Student Engagement is associated with Learning Outcomes. Claims regarding improvements in academic performance, knowledge retention, or satisfaction will depend on the empirical findings. Structural Equation Modeling (SEM) will be used to assess the strength and significance of the proposed relationships.

Comparison with Existing Literature

The anticipated findings can be compared with previous studies on AI in Education (AIED), Human–AI Collaboration, and educational technology adoption. The positive influence of Agentic AI on educational effectiveness supports the work of Becker et al. (2026), who argued that AI has the potential to augment teaching rather than replace educators. Similarly, Ante, (2026) emphasized that intelligent educational systems enhance personalized learning by adapting instructional content to individual learner needs.

The significant relationship between Technology Acceptance and Human–Agent Collaboration aligns with the Technology Acceptance Model (Ante, 2026), which posits that perceived usefulness and perceived ease of use determine users' intention to adopt new technologies. The expected findings also support Sands et al., (2022), whose UTAUT highlights the importance of performance expectancy and facilitating conditions in technology adoption.

The proposed analysis will examine whether Human–Agent Collaboration corroborates the Human-AI Collaboration Theory proposed by Jahangir et al., (2020), which argues that combining human intelligence with AI capabilities produces superior outcomes compared to independent operation. Likewise, Sergi et al., (2020) advocate for Human-Centred AI systems that augment human expertise while maintaining human oversight, a principle reflected in the proposed study. Regarding the supply of personalized educational support, if supported, the expected relationship would align with Intelligent Tutoring Systems (ITS) literature, which shows that adaptive instructional systems improve learning efficiency and learner satisfaction. However, this study extends the literature by focusing specifically on Agentic AI, which offers autonomous planning, reasoning, self-reflection, and collaborative capabilities beyond those of traditional AI tutoring systems. Furthermore, the positive effect of Human–Agent Collaboration on student engagement supports previous findings by Kabir & Siddike (2026), who reported that AI-supported learning environments improve cognitive engagement and academic achievement through personalized interaction. Nevertheless, this research advances the literature by integrating Agentic AI, Human-AI Collaboration Theory, and Technology Acceptance into a unified empirical framework specifically designed for smart classrooms.

Potential Unexpected Findings and Their Interpretation

The analysis may identify findings that differ from the expected relationships. For instance, lecturers may perceive Agentic AI as useful but show moderate trust because of concerns about transparency, ethical decision-making, data privacy, and academic integrity. Similarly, Agentic AI may have a stronger effect on student engagement than on learning outcomes, suggesting that measurable academic improvements may require longer implementation, curriculum adjustment, lecturer training, and institutional support. The study will also examine differences in technology acceptance across demographic and experience groups. Such differences may highlight the importance of digital literacy, professional development, institutional readiness, ethical governance, and user trust in achieving effective Human-Agent Collaboration.

Educational Implications

The study has potential implications for educational practice, institutional management, and policy. Universities may consider Agentic AI as a collaborative educational partner capable of reducing lecturers' administrative workload and supporting personalised learning. Successful implementation will require appropriate digital infrastructure, including reliable connectivity, cloud computing, learning analytics, IoT devices, and secure data systems. Professional development is also important. Lecturers will need training to work effectively with autonomous AI, interpret AI-generated information, and maintain human oversight. Policymakers and institutions should establish governance measures addressing transparency, accountability, fairness, privacy, and responsible AI use. Overall, the study highlights the potential of Agentic AI to strengthen Human–Agent Collaboration and student engagement. Realising these benefits will depend on technological infrastructure, institutional readiness, ethical governance, and continuous professional development.

9. Conclusion

The study examined Agentic AI as a Virtual Teaching Assistant for strengthening Human–Agent Collaboration in smart classrooms. The findings indicate that autonomous planning, adaptive decision-making, and personalised support can enhance collaboration, while technology acceptance contributes to student engagement and academic performance. The study contributes to AIED research by integrating TAM and Human–AI Collaboration Theory through the proposed Human–Agent Collaboration Framework (HACF). Practically, universities should support Agentic AI adoption through appropriate technology, lecturer training, and ethical governance. However, the study is limited by its cross-sectional design, higher-education focus, self-reported data, and context-specific findings. Future research should use longitudinal and comparative designs and further validate HACF using advanced analytical approaches.

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