

WALSH UNIVERSITY'S

Inspirations in AI Innovation



AI

Volume 2

Walsh University's Inspirations in AI Innovation

Volume 2

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Table of Contents

Letter from the Editors.....	3
A Comparative Study of Agentic and Generative AI for Physical Therapy Treatments Scoping Physician, Therapist, and Marketing Methods	4
Revolutionizing Ripples: Agentic AI Empowering Sustainable Catfish Farming in Ghana	8
Exploring Preservice Teachers’ Artificial Intelligence Competence in Ghana	12
The Transformative Role of Agentic AI in Ghanaian Processing Plants: An Interdisciplinary Imperative	15
STEM Students’ Behavioural Intention to Use Collaborative Robots for Learning and Innovation in Ghana	19
Agentic AI in Economics Education: Fostering Autonomous and Empowered Learning.....	21
From Ethical Awareness to Social Good: A Model of Responsible AI among Higher Education Students	24
Performance Evaluation of Time-Series Forecasting for Industrial Equipment Degradation using SARIMA and Machine Learning Models on NASA PHM Datasets	26
Generative AI Use and Self-Regulated Learning among Economics Students	29
Generative AI Use and Critical Thinking among Economics Students.....	31
Modelling Preservice Teachers’ Intention to Integrate GenAI in Teaching	33
Meal Planning and Food Waste Reduction Through Artificial Intelligence.....	35
Is AI-Prompted Engineering for Graduate Nursing Students?	39
Agentic AI for Global Sight: Promoting Mobility for All in Africa, USA, and Beyond.....	42
Black Women and AI: Past and Contemporary Perspectives	46
Economics Students’ Curiosity, AI-Driven Self-Regulated Learning and Learning Performance: A Mediation Model.....	49
Assessing Acne Management Products Through Clinical and Consumer Perspectives Using ChatGPT ..	53
Evaluating AI Rendering for the Next Generation of Architects.....	56
AI for Architecture & Environmental Analysis	59
Artificial Intelligence in the Synthesis of Human Personality	62
Developing a Revised Framework to Better Utilize AI to Improve the Research Process.....	64
Beyond the Replication: Modeling and Environmental Effects	67
Artificial Intelligence for Food Safety: Strengthening Protection from Farm-to-Table	70
Enhancing Actuarial Science Education and Practice Through Artificial Intelligence	74
Democratizing AI: Running Large Language Models on Raspberry Pi	77
Modelling the Nexus between AI Literacy and Problem Solving Skills among University Students in Ghana.....	85

Letter from the Editors

Inspiration in Faith and Innovation: A Collaborative Commitment to Academic Excellence

This publication is born from a shared mission, a calling to serve students through the pursuit of academic excellence, always in harmony with *Walsh University's* Catholic identity and institutional mission. *Walsh University*, in collaboration with the *University of Cape Coast*, continues to foster academic excellence and innovation across diverse contexts.

Walsh University has been recognized by the *Cardinal Newman Society* for its fidelity to Catholic education. The *University of Cape Coast* is a premier higher education institution in Ghana and Africa, recognized as the *Africa Outstanding University of the Year at the 2026 Africa Education Summit*. Also, the *University of Cape Coast* was ranked *first in Ghana and West Africa and eleventh in Africa in the 2025 Times Higher Education rankings*. Building on this shared foundation, we envisioned a space where faith and intellect converge, and where students, faculty, and researchers alike can give voice to their ideas, discoveries, and innovations. Today, we are humbled and grateful to present *Walsh University's Inspirations in AI Innovation, Volume 2*. This work is more than a collection of research; it is a testament to the boundless creativity that God has placed in the human spirit. Guided by His wisdom, we seek to cultivate innovation not merely for its own sake, but as a means of service to improve lives, expand knowledge, and inspire the next generation of scholars across the globe.

We honor the dedication of the authors whose contributions fill these pages, and we encourage them to continue pursuing truth with courage, excellence, and humility. We also extend our heartfelt gratitude to *Walsh University* for its steadfast support in making this scholarly work possible.

May this volume ignite new ideas, deepen faith, and strengthen our shared resolve to transform education and research for the greater good. May God's blessings accompany you at every step of your academic journey.

With hope and inspiration,

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A Comparative Study of Agentic and Generative AI for Physical Therapy Treatments Scoping Physician, Therapist, and Marketing Methods

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Many patients enter physical therapy with severe bruising post injury, such as falls and accidents. As a physical therapist, it is important to treat the skeletal muscular issue with stretches, exercises and interventions. Bruising from injuries can also cause the patient an additional level of pain and discomfort; therefore, adding topical bruise care into treatment plans would improve patient care overall.

Regarding topical medications, consulting with a physician can help to obtain a full understanding of the medication's use, effectiveness, and possible side effects. Understanding the active ingredients and their function in medications promotes effective patient treatment by accurately targeting the bruising with topical products.

Utilizing chemical terms and emphasizing active ingredients can market products effectively and efficiently. A product should appeal and focus on physical therapy clinics, rehabilitation centers, and pharmacies. Marketing methods, such as video advertisements and package design, can make an impact on consumers and patients alike.

The innovation of bruise care from therapy, physician and marketing perspectives was analyzed using both agentic and generative AI. The agent mode of Grok AI and ChatGPT's generative AI created bruise control products with physical therapy treatment, clinical, and marketing methods in consideration.

Researcher 1 asked generative AI (ChatGPT 5.1) and agentic AI (Grok 4) the following prompt related to physical therapy, bruising and skin assessment:

Explain how this AI system can support physical therapists in assessing bruising, guiding treatment decisions, monitoring healing progress, and improving patient outcomes when using a topical skin-care treatment. Describe the key features, benefits for PT practice, and real-world scenarios where it would be most useful.

While both AI models address the key parts of skin assessment, the approach and depth differed. The results showed that generative AI was much better for broad use, giving less specific and detailed statistics and medical jargon that may be better for patient use for image-based assessment, treatment guidance and patient education support. Agentic AI uses an analytical approach giving detailed stats that may be better for physical therapist or physician use for data-driven decisions, remote monitoring and objective quantitative results.

This data demonstrates how both of these AI models can be used for two distinct roles in physical therapy and bruising skin care. Generative AI shines in patient use while Grok AI gives necessary data for clinical reasoning. In the future, a hybrid model of these AI systems may be able to offer the ease of use of Generative AI but also the clinical reasoning of agentic.

Researcher 2 found that when asked from a physician's perspective, generative AI and agentic AI took similar approaches when designing formulas for a cream, gel, and a serum all aimed to treat bruising post injury. Both generative AI via ChatGPT 5.1 and agentic AI via Grok 4 expert mode were given the following prompt:

You are a physician working alongside a physical therapist developing a product that can help with the healing process of bruising. What are good active ingredients I should use in my product? Make one for a cream, gel and serum.

Generative AI via ChatGPT 5.1 for the cream, gel, and serum selected ingredients including Vitamin K, Arnica, Vitamin C, Bromelain, and Horse chestnut. While these ingredients are clinically sound, this generative AI gave broad recommendations lacking specific concentrations or advanced justifications for each ingredient. Agentic AI via Grok 4 expert mode suggested similar ingredients but included concentrations for each ingredient and deeper clinical rationale. The agentic AI gave physician-level formulations that were more clinically effective and tailored for the different stages of bruising. Overall, agentic AI proved to be more clinically useful for physicians by giving carefully calculated formulas and strong rationale compared to generative AI. Generative AI gave broad formulas that lacked concentration-level details and showed limited creativity that would prove to be of little help for physicians.

Researcher 3 explored the capabilities of both generative AI (ChatGPT) and agentic AI (Grok expert mode) from a marketing perspective. The prompt used in these trials is given below.

I am evaluating the capabilities of generative AI innovation of bruise care from a marketing perspective. Please help me create a topical bruise care product for incorporating into treatment plans for physical therapy patients that would overall improve patient care. Please create an image for me along with 3 bullet points describing the advantages of the design. Please make the packaging appealing, professional, and softer fonts to encourage a positive tone.

Trials revealed that Grok’s expert mode with embedded agentic AI capabilities provided the most visually appealing designs and detailed bullet points. Professional fonts and eye-catching images were included as well. The AI-generated image is shown in Fig. 1. The best features were highlighted with these AI-driven bullet points:

- **Appealing Visuals for Patient Engagement:** The soft blue color scheme and rounded bubble elements create a calming, approachable aesthetic that reduces intimidation for patients recovering from injuries, encouraging consistent use in their treatment plans.
- **Professional Yet Gentle Typography:** Using softer, rounded fonts conveys trustworthiness and empathy, aligning with physical therapy’s focus on healing and support, which helps build a positive association with the product.
- **Informative and User-Friendly Layout:** Clear icons, before-and-after imagery, and concise benefit checklists make the packaging easy to understand at a glance, empowering patients and therapists to integrate it seamlessly into care routines for improved outcomes.

Figure 1. Bruise care product image. (created by Grok)



In comparison, ChatGPT generative AI mode provided a design with no misspellings and a visual representation of a bruise, but it lacked a wide range of color. The packaging of the product lacked detail and an engaging tone. As given in the findings, agentic AI performed better than generative AI in regard to product design. This study showcases the effectiveness of agentic AI in bruise care and patient engagement.

The innovation of bruise care from therapy, physician and marketing perspectives was analyzed using both agentic and generative AI. The agent mode of Grok AI and ChatGPT’s generative AI created bruise control products with physical therapy treatment, clinical, and marketing methods in consideration. ChatGPT’s generative AI provided broad, easy to understand information that is

best suited for patient education and general packaging design. The agent mode of Grok AI proved to be more clinically and professionally effective because it provided more detailed statistics and data as well as stronger formulations for healthcare professionals. Finally, from a marketing standpoint, it gave more visually appealing packaging for consumers.

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Grok AI: grok.com

ChatGPT: www.chatgpt.com

Revolutionizing Ripples: Agentic AI Empowering Sustainable Catfish Farming in Ghana

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Introduction

Aquaculture has become a vital solution to food insecurity and unemployment in developing countries. In Ghana, household-based catfish farming initiatives have been introduced to empower families with income-generating opportunities. However, despite the provision of tanks, feed, and training, many households experience high fish mortality, leading to wasted resources and frustration. This project explores how Artificial Intelligence (AI) can be applied to improve aquaculture practices, reduce losses, and enhance sustainability.

Project Highlights

The aim of the project is to design and implement AI-driven solutions that reduce fish mortality, increase productivity, and promote sustainable household aquaculture in Ghana. The objectives include exploring the possibilities for applying AI-based monitoring for real-time water quality management, using predictive analytics for early detection of diseases, developing automated feeding systems that optimize growth and reduce waste, and implementing early warning alerts for environmental stress factors.

Research Strategies

The methodology involves collecting information for a foundation for current processes and then utilizing agentic AI to create solutions for these challenges. Several recent studies and projects have explored AI, Internet of Things (IoT), and digital tools in aquaculture, including water-quality monitoring, disease prediction, and automated feeding (Zheng et al., 2020). However, most work has focused on larger-scale or regionally generalized systems rather than household-level catfish farming in Ghana. Representative examples include risk management frameworks for Ghanaian catfish farming that recommend monitoring and IoT for water quality and disease risk but typically stop short of deploying predictive AI models and automation at the household level (Akinyemi, & Okoro 2023; FAO 2022; Ofori & Dankwa 2021). Regional AI systems such as Fish-NET have applied computer vision and aerial imagery for pond monitoring in West Africa, yet they target commercial or research-scale operations rather than small household farms (Salako, 2024). Systematic reviews show growing use of AI methods in aquaculture for disease detection, feeding optimization, and water-quality prediction, but emphasize a lack of applied studies in low-resource, smallholder settings. Low-cost IoT experiments in Ghana have demonstrated feasibility for water monitoring, but integration with predictive AI and automated feeding remains limited in

household contexts (Rather, 2024; Son, 2024). Recent engineering work has produced automated fish-feeding systems and AI models for feeding optimization, yet these are often tested in controlled or commercial environments, not household-scale trials that consider local constraints like cost, power, and maintenance (Rather, 2024; Son, 2024).

Next, the authors conducted experimental trials using Grok's expert mode to determine how agentic AI can assist researchers in serving the common good in aquaculture. More specifically, a prompt was designed to create a brief action plan for farmers and identify free agentic AI tools that are accessible across Ghanaian communities, particularly focusing on strategies for sustainable household catfish farming. The agentic AI data is shown below. Gamma AI produces representations of catfish farming in Ghana as shown in Figures 1-2.

Agentic AI Trial 1: Four-Step Action Plan

Step 1: Assess Farm Needs

Identify key challenges in household catfish farming, such as water quality, feed optimization, disease detection, and market access. Use agentic AI to analyze farm data via mobile apps for personalized diagnostics. Engage local experts to validate AI insights, ensuring sustainability in Ghana's climate.

Step 2: Integrate AI Tools

Adopt free agentic AI platforms to automate monitoring. Set up sensors or apps for real-time data on pond conditions; AI agents plan feeding schedules and predict harvests. Train family members on simple interfaces to sustain operations without constant oversight.

Step 3: Implement and Monitor

Launch AI-driven actions like automated alerts for pH imbalances or growth tracking. Agentic systems autonomously adjust variables, optimizing yields. Track metrics like fish survival rates and costs over 3 months, comparing to pre-AI baselines to demonstrate efficiency gains.

Step 4: Scale and Share

Expand successful AI strategies to community farms, hosting demos on improved yields and reduced labor. Use agentic AI for market forecasting to boost income. Document results in local networks to advocate for broader adoption, highlighting environmental benefits like water conservation.

Agentic AI Trial 2. Two Free Tools

ChatGPT (OpenAI): Free agentic AI chatbot for multi-step planning, querying aquaculture advice, and simulating farm scenarios accessible via mobile in Ghana.

Google Gemini: Free AI with agentic features for real-time data analysis, disease prediction, and customized catfish farming guides, usable on any internet device.

Figure 1. A representation of catfish farming in Ghana. (image created by Gamma)



Figure 2. A representation of the positive impact of AI technology on catfish farming in Ghana (image created by Gamma)



Conclusion

Agentic AI advances aquaculture by enabling autonomous decision-making, optimizing resource use, and enhancing sustainability in catfish farming. It serves the common good through predictive analytics for disease control, yield maximization, and climate adaptation, reducing food insecurity in countries like Ghana. Essentially, through equal access, it empowers smallholders with necessary resources and paves the way for resilient global food systems.

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Exploring Preservice Teachers' Artificial Intelligence Competence in Ghana

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The rapid advancement of artificial intelligence (AI) technologies is transforming education worldwide, creating both opportunities and challenges for teaching and learning (Arthur, 2026; Nsoh et al., 2023). As AI becomes integrated into educational systems, the preparation of competent teachers who can navigate these technologies has become essential (Karsenti et al., 2019; Zou et al., 2025). This need is particularly relevant in developing countries like Ghana, where technological advancements can significantly enhance educational development (Parry & Viviers, 2023). Preservice teachers will play a significant role in incorporating AI into their classrooms, yet research shows their competence varies across technological knowledge, pedagogical skills, and ethical considerations (Ayanwale et al., 2024; Mikeladze et al., 2024; Salifu et al., 2025). While Ghanaian preservice teachers recognize AI's potential benefits, they often express anxiety about using these tools (Butakor et al., 2023; Falebita, 2025; Abreh et al., 2025). Therefore, this study uses a latent profile and network analysis to explore the distinct patterns of AI competence among preservice teachers.

The study sampled 509 preservice teachers in Ghana using a purposive sample. The self-determination theory, social cognitive theory, and the digital competence frameworks underpinned this study (Bandura, 1999; Demirtaş & Mumcu, 2021; Li et al., 2025). A descriptive cross-sectional survey design was used to assess AI competence across six domains (Ahmad et al., 2025; Shi, 2025). Each domain in this study is rooted in these theoretical perspectives. The study utilized an adapted survey instrument with a five-point Likert scale to ensure reliability and construct validity for the Ghanaian context. Analytical procedures included latent profile analysis to identify distinct competence profiles and network analysis to explore interrelations among competence dimensions (Creswell & Guetterman, 2019; Rosenberg et al., 2021).

The study showed that preservice teachers demonstrate high competence in AI across all six domains, with two distinct latent profiles identified: very high all-round competent teachers and high competent teachers. The network analysis highlighted that pedagogy and assessment competencies are central to the AI competence system, while ethical and professional engagement indicators remain peripheral, indicating areas for targeted improvement. Furthermore, the AI competence structure appears coherent yet uneven, showcasing strong knowledge and pedagogy nodes but fragmented integration of ethics and human-centred education. This suggests an imbalance in competence development and low clustering coherence within the competencies, limiting the effectiveness of a holistic AI education framework.

The findings have practical implications for policymakers, teacher educators and teacher preparation reforms, emphasizing the need to enhance AI knowledge, ethics, and human-centred competencies within teacher education programs. Policymakers should implement differentiated

professional development programs and ensure that pedagogy, assessment, and application skills are integrated into a coherent AI competence framework.

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The Transformative Role of Agentic AI in Ghanaian Processing Plants: An Interdisciplinary Imperative

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Abstract

This project was designed by professional researchers and student researchers to reveal the newest technological advancement in AI, agentic AI, to serve the common good in the Ghanaian farming industry. Grok, with an embedded agent mode, was utilized to identify background, tools, description, plant/company, success metrics, and limitations to agentic AI. One tool that stood out in performance was CocoaSense AI. Diving deeper, research revealed that CocoaSense positively impacted cocoa yields and tripled the harvest up to 1,500 kg/year per farmer. (Cropin 2025) This researcher highlighted the benefit of utilizing CocoaSense in today's Ghanaian agricultural ecosystem.

Introduction

The integration of Artificial Intelligence (AI) into the industrial landscape of West Africa represents a strategic imperative for economic survival and workforce readiness. Research at the intersection of industrial chemistry and economics shows that Agentic AI is particularly vital for Ghanaian processing plants (Brew et al., n.d.). Agentic AI refers to autonomous systems capable of perceiving and acting without constant human intervention. This interdisciplinary synergy equips professionals to navigate contemporary industrial systems within the cocoa sector (Brew et al., n.d.). The adoption of these technologies extends beyond modernization as it is a strategic necessity for sustaining the competitiveness of the industrial future of Ghana (Aryee et al., 2025).

The Agentic AI Shift in Cocoa Processing

The theoretical potential of AI has transitioned into a reality and an operational necessity. In the Western Region of Ghana, platforms such as CocoaSense exemplify this shift by proactively executing tasks that range from real-time farm data extraction to deploying drone monitoring (Brew et al., n.d.). This capability is crucial for addressing local challenges like climate volatility. Data indicates that Agentic AI implementation can triple cocoa yields from approximately 500 kg/ha to 1,500 kg/ha (Cropin, 2025 & Brew et al., n.d.). Furthermore, predictive execution by these agents reduces post-harvest losses by 25% (Cropin, 2025 & Brew et al., n.d.). An example of the AI technology used in cocoa fields is shown in Figure 1. Realizing these gains requires a workforce skilled in both chemical optimization and economic modeling (Sheikh et al., 2025).

Figure 1. AI Technology for Cocoa Processing (Gamma AI)



Industrial Chemistry: Precision and Optimization

The team provides specialized industrial chemistry knowledge throughout the project. From an industrial chemistry perspective, AI is the pivot point for enhanced efficiency. At facilities such as Plot Ghana in Mpintsin and Niche Cocoa Industry Ltd in Tema, researchers utilize AI to simulate fermentation recipes to cut defects by 20% (Brew et al., n.d.). Specific case studies at Niche Cocoa prove how AI-augmented Energy Management Systems optimize utility usage to align with sustainability goals. Career readiness now demands expertise in sensor calibration to translate AI insights into tangible processing improvements (Mann et al., 2025). An example of industrial chemistry applications is shown in Figure 2.

Figure 2. Industrial Chemistry Applications for Cocoa Processing (Gamma AI)



Economics: Resilience and Market Forecasting

Another unique part of this research includes the incorporation of economics perspectives by the team. Economic analysis complements this technical precision by mitigating risk. Agentic AI tools provide economists with the predictive capacity to forecast supply disruptions and slash economic

losses by an estimated 15% (Cropin, 2025 & Brew et al., n.d.). Agents analyze yield data via platforms like CocoaSense to optimize sales timing and secure premium prices via certifications (Cropin, 2025 & Brew et al., n.d.). Consequently, the modern economist must master supply chain analytics to guide policy and ensure income stability (Liu et al., 2024). Figure 3 shows how agentic AI can benefit economic analysis.

Figure 3. Agentic AI Tools & Economic Analysis (Gamma AI)



This research benefits students in critical career readiness skills related to industrial chemistry and economics through the use of agentic AI for societal issues. More specifically, researchers focused on two plants in Ghana: Plot Ghana (Mpintsin, Western Region, Ghana) a plant for processing cocoa liquor, and Niche Cocoa Industry Ltd (Tema, Greater Accra, Ghana) a plant for processing cocoa liquor as well as finished products such as refined chocolate, chocolate drinks, and chocolate spreads. Our work addresses cocoa industry challenges, aligning with regional sustainability and economic goals, by integrating AI-driven solutions like CocoaSense to enhance societal benefits.

This study supports researchers in industrial chemistry and economics with important career readiness skills in AI applications, thereby fostering innovative solutions for Ghana's cocoa industry that aligns with regional sustainability and economic goals.

Conclusion: A Unified Workforce for the Future

The convergence of industrial chemistry and economics through AI offers a robust framework for the industrial future of Ghana. The CocoaSense model illustrates that the value chain benefits when chemists optimize resource efficiency to reduce water and pesticide use by 20% (Mensah et al., 2023). To prevent Ghana from falling behind in the Fourth Industrial Revolution, academic and industrial entities must collaborate to train a workforce capable of deploying these autonomous systems (Sinde et al., 2023). By equipping professionals with these advanced skills, Ghana can secure a resilient and economically viable cocoa processing industry that serves the common good.

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STEM Students' Behavioural Intention to Use Collaborative Robots for Learning and Innovation in Ghana

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The adoption of collaborative robots (cobots) in secondary STEM education offers new possibilities for enhancing hands-on learning, creativity and technological innovation (Adjekum & Asare, 2025), yet students' willingness to use them depends on key cognitive, motivational and contextual factors (Abreh et al., 2025; Amenyo & Kpo, 2023). This study examined the behavioural intention of Senior High School Science, Technology, Engineering and Mathematics (STEM) students in Ghana to adopt cobots for learning and innovation, focusing on determinants that facilitate or constrain acceptance. Cobots are particularly relevant to STEM learning because they support experimentation, automation tasks, engineering design, problem-solving and interactive demonstrations that strengthen conceptual understanding and technical skills (Yang et al., 2023; Twum-Antwi, 2024). For STEM students, these capabilities promote innovation, teamwork and higher-order thinking, which are essential for success in emerging digital and AI-driven environments.

A total of 387 STEM students participated in the study. The conceptual model was informed by core constructs from technology acceptance research and extended with task–technology fit and individual–technology fit, reflecting recent advances in educational technology adoption studies (Arthur et al., 2025; Acquah et al., 2025; Parviz & Arthur, 2025; Salifu et al., 2025; Salifu et al., 2024). A variance-based Structural Equation Modelling (PLS-SEM) approach was applied to examine the relationships among the predictors of behavioural intention.

The PLS-SEM results showed that effort expectancy, hedonic motivation, social influence and performance expectancy significantly and positively shaped students' behavioural intention to adopt cobots, with effort expectancy emerging as the most influential determinant. Task–technology fit strongly predicted individual–technology fit, which in turn significantly enhanced behavioural intention. These findings highlight the importance of ensuring that cobot functionalities align with STEM learning tasks, and that students perceive the technology as easy to use, enjoyable and beneficial.

These results have practical implications for teachers, educational leaders and technology developers. They point to the need for supportive learning environments, training programmes and institutional strategies that build students' confidence, enhance usability and increase exposure to robotics. Most importantly, the findings emphasise the combined effects of technological fit, social support and students' affective responses in shaping cobot readiness. By using a robust analytical

approach grounded in contemporary educational technology research, this study contributes to a deeper understanding of emerging robotics adoption in STEM education.

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Agentic AI in Economics Education: Fostering Autonomous and Empowered Learning

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Introduction

The transformative potential of Artificial Intelligence (AI) in education extends beyond automation and efficiency, toward empowering learners with agency (Arthur, 2026; Arthur et al., 2025). Traditional AI in education, such as automated grading systems or learning analytics dashboards, primarily supports educators by executing predetermined tasks (Parviz & Arthur, 2025). Generative AI, including tools like ChatGPT, produces content or answers based on user prompts but lacks proactive engagement with the learner’s goals (Salifu et al., 2025). In contrast, agentic AI operates with a degree of autonomy, assessing learners’ progress, providing personalized scaffolding, suggesting next steps, and fostering reflective and decision-making skills (Lai et al., 2025; Yan, 2025). In Economics education, where conceptual understanding, critical thinking, and applied problem-solving are essential (Acquah et al., 2025; Arthur, Yidana et al., 2025), agentic AI can cultivate autonomous and empowered learners. This paper focuses on the role of agentic AI in Economics education, where students are not passive recipients of information but active participants in constructing and applying knowledge.

Key Distinctions between Traditional, Generative, and Agentic Artificial Intelligence Paradigms

Artificial Intelligence (AI) has evolved through several major stages. While Traditional AI relies on explicit programming and rule-based systems, newer paradigms like Generative AI and Agentic AI introduce capabilities like content creation and autonomous decision-making. Table 1 outlines the fundamental differences in role, learner autonomy, adaptivity and critical thinking support across these three AI types.

Table 1: Key Distinctions between Traditional, Generative, and Agentic Artificial Intelligence Paradigms

Feature	Traditional AI	Generative AI	Agentic AI
Role	Task execution (grading, reminders)	Content creation (essays, explanations)	Active guidance and decision support
Learner Autonomy	Low	Moderate	High
Adaptivity	Static	Limited	Dynamic, goal-oriented
Critical Thinking Support	Minimal	Indirect	Directly fosters reflection and problem-solving

Agentic AI in Senior High School Economics Education

In senior high school, students often struggle with abstract concepts such as market structures, fiscal policies, and economic modeling. Agentic AI can:

1. **Adaptive Learning Pathways:** Based on students' performance in simulations of supply-demand models, agentic AI suggests personalized exercises, alternative explanations, or interactive case studies.
2. **Decision-Based Simulations:** For example, in a fiscal policy simulation, the AI can pose economic dilemmas and guide students through the consequences of different tax or spending decisions, fostering critical reasoning.
3. **Self-Regulation and Reflection:** The AI prompts students to reflect on their choices and learning strategies, enhancing metacognitive skills.

Agentic AI in Higher Education Economics

In universities, where learners engage with complex economic theories and data-driven research, agentic AI can enhance learning through:

1. **Research Assistance:** Beyond generating summaries, agentic AI identifies gaps in a student's argumentation, suggests relevant datasets, and proposes advanced analytical methods.
2. **Project Management and Collaboration:** In group projects, the AI can allocate tasks based on individual strengths, monitor progress, and recommend peer discussions to resolve conceptual misunderstandings.
3. **Scenario Analysis:** Students can model macroeconomic policies using AI-generated simulations that adjust dynamically according to their input, fostering both autonomy and decision-making skills.

Conclusion

Agentic AI represents a transformative tool in Economics education, emphasizing learner autonomy, empowerment, and critical engagement. In both senior high school and higher education, its proactive, adaptive, and reflective capabilities bridge the gap between knowledge acquisition and applied economic reasoning. By moving beyond traditional and generative AI, agentic AI not only enhances learning outcomes but also cultivates self-directed, confident, and analytically skilled learners.

Practical Implications and Recommendations for Integrating Agentic AI in Education

Table 2 summarizes the practical implications of integrating agentic AI into the education system, particularly for Economics, and provides corresponding recommendations for implementation across different educational levels and roles.

Table 2: Practical Implications and Recommendations for Integrating Agentic AI in Education

Context	Practical Implication	Recommendation
Senior High School	Personalized simulations and reflective prompts	Integrate AI-driven economic simulations and scaffolded reflection exercises
Higher Education	Advanced scenario modeling and research support	Employ agentic AI in research projects, group tasks, and policy modeling courses
Curriculum Development	Focus on autonomous learning and critical thinking	Redesign Economics curriculum to leverage AI's agentic features, promoting metacognitive skills
Teacher Role	Shift from content delivery to facilitation	Train educators to guide AI-supported learning while monitoring learner autonomy

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From Ethical Awareness to Social Good: A Model of Responsible AI among Higher Education Students

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The ethical dimensions of artificial intelligence (AI) are becoming central to higher education, where students are being prepared to engage with emerging technologies responsibly (Acquah et al., 2025; Salifu et al., 2025). This study examines how ethical awareness translates into socially beneficial AI use by modeling the relationships among human autonomy, beneficence, fairness, AI ethical awareness, AI critical evaluation, and AI for social good (ASG). The focus is on Ghanaian higher education students, where AI adoption is expanding but ethical engagement remains underexplored (Arthur et al., 2025; Arthur, 2026; Kwakye et al., 2025). Understanding these pathways is critical to fostering responsible AI behavior that aligns with ethical principles and societal benefit.

Purposive sampling was utilized to select a total of 509 higher education students who participated in the study, providing insights into how ethical principles shape AI engagement. The conceptual framework draws on the Theory of Planned Behavior (Ajzen, 1991), Ethical Decision-Making Theory (Rest, 1986), and the Social Cognitive Theory (Bandura, 1986) to link ethical values with cognitive evaluation and behavior. Data were analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to test hypothesized relationships among the constructs, ensuring robust assessment of both direct and mediating effects (Arthur et al., 2025). The model captures how human autonomy, beneficence, and fairness contribute to ethical awareness, critical evaluation, and ultimately, AI use for social good.

Results indicate that human autonomy and fairness significantly enhance AI ethical awareness, while beneficence does not. Ethical awareness strongly predicts AI critical evaluation, which emerges as the most influential driver of AI for social good. Fairness also contributes significantly to critical evaluation, whereas beneficence, although not predictive of awareness or evaluation, directly promotes AI for social good. These findings highlight that these ethical principles operate through both cognitive pathways, via awareness and critical evaluation, and direct motivational pathways, shaping students' responsible engagement with AI.

The findings have important implications for educators, curriculum designers, and policymakers. Integrating ethics into AI education, emphasizing critical evaluation, and reinforcing fairness and autonomy can strengthen students' ability to leverage AI for societal benefit. The study contributes

a multidimensional understanding of responsible AI engagement in higher education, providing evidence that ethical awareness and critical evaluation are pivotal for translating ethical principles into socially beneficial behavior. By focusing on Ghanaian students, the research also extends knowledge in underexplored African contexts, informing future AI ethics education and policy development.

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Performance Evaluation of Time-Series Forecasting for Industrial Equipment Degradation using SARIMA and Machine Learning Models on NASA PHM Datasets

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Abstract

This paper examines the performances of standard statistical techniques (SARIMA and ARIMA) and differences with modern machine learning methodologies (Random Forest, LSTM, CNN-LSTM, and Attention-LSTM) used for remaining useful life (RUL) prediction in turbofan engines, NASA PHM (Prognostics and Health Management) C-MAPSS datasets. Specifically, we found an improvement, as measured by RMSE, of 60% in accuracy using Attention-LSTM over SARIMA-based inferencing methods. This study will offer benchmarking performance for predictive maintenance researchers.

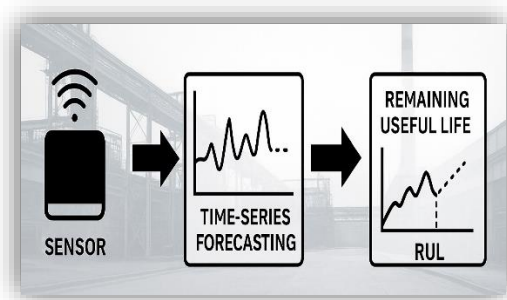
Keywords

LSTM, Equipment degradation, Predictive maintenance, Remaining useful life.

Introduction

The advent of sensor technologies and data analytics has enabled the development of sophisticated predictive maintenance systems that can forecast equipment failures before they occur, especially in critical applications like the aerospace industries, where unexpected failures can result in significant economic losses and safety hazards [1]. Time-series forecasting models play a pivotal role in these systems by analysing temporal patterns in sensor data to predict the remaining useful life (RUL) of critical components. The NASA Prognostics and Health Management (PHM) datasets, particularly the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) data, have emerged as the gold standard for evaluating prognostic algorithms [2], [3].

Figure 1. Time Series Forecasting process (freepik.com)



Literature Review

Traditional statistical methods such as AutoRegressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) have been extensively used for time-series forecasting in industrial applications [4]. Recent advances in machine learning, particularly deep learning architectures, have shown promise in addressing these limitations. Long Short-Term Memory (LSTM) networks have demonstrated superior performance in modelling sequential data with long-term dependencies[5].

Research Objectives

This study aims to:

1. To evaluate SARIMA, ARIMA, Random Forest, LSTM, CNN-LSTM, and Attention-LSTM models on the datasets.
2. To quantify the performance improvements achieved by modern machine learning approaches over traditional statistical methods

Methods

Figure 2. Evaluation of Statistical vs Machine Learning Models (freepik.com)



Dataset Description

The NASA C-MAPSS dataset consists of four sub-datasets. Each dataset contains multivariate time series from 21 sensors and 3 operational settings, recording turbofan engine behaviour from healthy state to failure. Data preprocessing was done like normalisation, Feature Selection, Windowing and RUL Target Function. The statistical models like ARIMA and SARIMA were compared with machine learning models like Random Forest, LSTM, CNN-LSTM and Attention-LSTM.

Performance Metrics

Model performance was evaluated using three standard metrics:

- **Root Mean Square Error (RMSE)**
- **Mean Absolute Error (MAE)**
- **Coefficient of Determination (R^2)**

Lower RMSE and MAE values indicate better forecasting accuracy, while higher R^2 values indicate better model fit.

Results & Discussion

Figure 3. Overall comparison of various Time Series Forecasting Techniques

Model	RMSE	MAE	R ²
Attention-LSTM	11.6	9.2	0.93
CNN-LSTM	12.8	10.1	0.91
LSTM	13.4	10.5	0.89
Random Forest	16.2	12.8	0.82
ARIMA	27.3	21.5	0.64
SARIMA	28.5	22.1	0.62

Overall Performance Comparison

Deep learning approaches consistently outperformed statistical and traditional machine learning methods across all evaluation metrics.

Conclusions

This comprehensive evaluation of time-series forecasting models on NASA PHM datasets provides clear evidence for the superiority of deep learning approaches in equipment degradation prediction. Key findings include the performance elevation in the order of highest to lowest.

CNN-LSTM > LSTM > Random Forest > SARIMA > ARIMA

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Generative AI Use and Self-Regulated Learning among Economics Students

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Artificial intelligence (AI) is no longer a futuristic concept confined to science fiction; it is an existing force reshaping every facet of modern life, including how we learn, teach, and conduct research (Arthur, 2026; Parviz & Arthur). From intelligent tutoring systems that adapt to individual learning paces to generative AI tools like ChatGPT that can draft essays or solve complex equations (Abreh et al., 2025). This study examined how expectancy value beliefs influence GenAI use and how such use, in turn, shapes self-regulated learning (SRL) among economics students in Ghana. GenAI is particularly relevant to economics education because it supports data analysis, content generation, model explanation, and structured academic writing (Acquah et al., 2025). These capabilities have the potential to strengthen students' analytical reasoning, independent learning, and strategic thinking when used appropriately.

A purposive sample of 416 undergraduate economics students from the University of Cape Coast participated in the study. The conceptual framework was grounded in Expectancy-Value Theory (EVT), which explains students' motivation in terms of expectancy (self-efficacy), intrinsic value, utility value, attainment value, and perceived cost (Eccles & Wigfield, 2002). GenAI use was positioned as a mediating variable linking motivational beliefs to self-regulated learning. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to test direct and mediating effects. Measurement reliability and validity were established using standard criteria, including composite reliability, average variance extracted, and discriminant validity.

The results showed that expectancy, intrinsic value, attainment value, perceived cost and utility value had significant positive effects on students' use of GenAI. GenAI use also had a significant positive effect on self-regulated learning, confirming its role as a learning aid when used purposefully. Furthermore, GenAI use significantly mediated the relationships between expectancy, intrinsic value, utility value, and SRL. These findings indicate that motivated students who perceive GenAI as useful and enjoyable are more likely to integrate it into their learning processes in ways that enhance goal setting, monitoring, and reflection. The results align with prior studies in Ghana showing that behavioural intention and perceived usefulness are central drivers of ChatGPT adoption and academic outcomes (Arthur et al., 2025; Salifu et al., 2025).

These findings have important implications for economics educators, instructional designers, and higher education policymakers. They highlight the need for structured AI literacy programmes that go beyond technical skills to include ethical use, metacognitive strategy development, and self-regulation. Rather than treating GenAI as a shortcut tool, universities should intentionally integrate it into coursework as a platform for planning, feedback, and reflective learning. By strengthening students' expectancy beliefs, enhancing task value, and reducing perceived cost, institutions can

ensure that the motivational “will” to use AI translates into the “wisdom” to learn. This study contributes to the emerging AI-in-education literature by offering a motivationally grounded explanation of how GenAI adoption supports self-regulated learning in economics education.

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Generative AI Use and Critical Thinking among Economics Students

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The increasing integration of generative artificial intelligence in higher education presents new opportunities for enhancing students' critical thinking; however, its impact depends largely on how continuously and ethically students engage with these tools (Howard & Sarbaum, 2022; Siegfried & Colander, 2021). This study assessed how continuous use of generative AI influences the critical thinking of economics students, with particular attention to knowledge processes, perceived trust, and ethics. In Economics education, AI use has been shown to enhance critical thinking skills and learning outcomes through digital and economic literacy, self-efficacy, and purposeful engagement with AI tools (Amala et al., 2025; Arthur, 2026; Zhang & Liu, 2025). However, excessive reliance on AI may weaken independent reasoning and reflective effort (Abbas et al., 2024).

A purposive sample of 433 economics students from a Ghanaian university participated in the study. The conceptual framework was grounded in Social Cognitive Theory, Technology Continuous Theory, and Critical Thinking Theory and incorporated the key constructs of Knowledge Acquisition, Knowledge Application, Knowledge Sharing, Perceived Trust, Ethics, Continuous Use and Critical Thinking. Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to test the measurement and structural models using SmartPLS version 3.0, which is consistent with recent empirical applications among economics students (Acquah et al., 2025; Salifu et al., 2025).

The PLS-SEM results revealed that Continuous Use (CUI), Knowledge Acquisition (KA), and Knowledge Sharing (KS) had significant positive effect on students' Critical Thinking (CRT), whereas Knowledge Application (KAP) did not exert a significant direct effect on CRT. Ethics (ET), Perceived Trust (PT), Knowledge Application, Knowledge Sharing had significant positive influence on Continuous Use (CUI), while Knowledge Acquisition did not significantly influence Continuous (CUI). Knowledge Acquisition had a strong positive effect on Knowledge Application, Knowledge Sharing, and Perceived Trust. Likewise, Knowledge Application positively influenced Knowledge Sharing and Perceived Trust. This underscores the interconnected roles of Knowledge Processes, Trust, and sustained AI engagement in shaping economics students' critical thinking outcomes.

These findings have clear implications for educators, instructional designers, and higher education institutions, highlighting the importance of structured and ethical AI integration that strengthens trust and supports core knowledge processes to enhance critical thinking. By linking continuous AI use with knowledge processes and critical thinking, this study provides a multidimensional view of AI-supported learning in economics education.

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Modelling Preservice Teachers' Intention to Integrate GenAI in Teaching

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The integration of Generative Artificial Intelligence (GenAI) in teacher education offers new possibilities for enhancing instructional design, assessment, feedback, and personalised learning, yet its adoption remains contingent on preservice teachers' perceptions, experiences, and ethical concerns (Arthur et al., 2025; Salifu et al., 2024). This study examined preservice teachers' behavioural intention to integrate GenAI applications into future teaching practice, with particular attention to experiential, affective, and risk-related factors that promote or inhibit adoption. GenAI is especially relevant to teacher education, as it supports lesson planning, content generation, formative assessment, and interactive pedagogical experimentation, thereby strengthening instructional competence and professional readiness. For preservice teachers, these affordances foster pedagogical creativity, reflective practice, and adaptive teaching skills required in increasingly AI-mediated educational environments.

A cross-sectional survey design was employed, drawing data from preservice teachers in higher education. The conceptual framework integrated the Technology Acceptance Model (TAM), UTAUT2, Expectation–Confirmation Theory, Trust–Risk theory, and Human–Computer Interaction (HCI) principles to explain GenAI adoption. Key constructs included perceived enjoyment, interactivity, perceived learning opportunities, perceived trust, perceived risk, satisfaction, and behavioural intention. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to assess the measurement and structural models, enabling robust evaluation of both direct and indirect relationships among constructs (Hair et al., 2022).

The PLS-SEM results revealed that perceived trust and perceived risk exerted significant direct effects on preservice teachers' behavioural intention to integrate GenAI, while satisfaction emerged as a strong positive predictor of intention. Perceived enjoyment, interactivity, and perceived learning opportunities did not exert strong direct effects on intention but significantly influenced intention indirectly through satisfaction. These findings highlighted satisfaction as a central post-adoption mechanism linking preservice teachers' GenAI experiences to their willingness to use the technology in future teaching.

The findings have important implications for teacher education institutions, curriculum designers, and policymakers. They emphasised the need to design engaging, interactive, and pedagogically

meaningful GenAI experiences that build trust while addressing perceived risks related to accuracy, bias, and academic integrity. Embedding structured GenAI training, ethical guidelines, and reflective practice within teacher education programmes may enhance satisfaction and foster sustained adoption. This study contributes a nuanced understanding of preservice teachers' GenAI adoption in educational contexts, by extending technology acceptance research through the integration of satisfaction and trust–risk perspectives.

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Meal Planning and Food Waste Reduction Through Artificial Intelligence

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Introduction

This project explored how everyday artificial intelligence tools can support healthier meal planning and food waste reduction using realistic household constraints. Rather than treating “smart fridges” as a premium technology limited to expensive appliances, the project tested whether common AI systems can reproduce similar value—meal planning, calorie estimation, and freshness-aware decision-making—using a standard refrigerator inventory and a smartphone.

Research Design

The research team designed a structured experiment around a real refrigerator dataset. They created a complete inventory, recorded expiration dates, and estimated “days fresh remaining” to reflect the reality of household food management. Items were grouped into practical categories (e.g., dairy, proteins, produce, leftovers, pantry goods) to make the inputs readable and consistent across systems. (Figure 1) This careful setup matters because research shows AI diet plans can vary widely depending on how prompts are framed and what constraints are included—especially when calorie targets are involved (Kaçar et al., 2025). Clear variable definitions helped keep comparisons fair: the independent variable was the AI system used, while dependent variables included item usage, waste-minimisation effectiveness, calorie consistency, and meal feasibility.

Using the same inventory and instructions, three systems—ChatGPT, Gemini, and Copilot—were asked to generate a 7-day meal plan averaging about 2,000 calories per day, prioritising foods closest to expiration and minimising waste. Each model produced full menus (breakfast, lunch, dinner, snacks), allowing the team to compare structured outputs rather than isolated recipe ideas. Their analysis echoed a broader theme in the food-waste literature: when AI is applied to inventory awareness and pattern recognition, it can reduce waste by “nudging” users toward timely consumption of high-risk items (Clark et al., 2025).

Figure 1. AI-generated food inventory (Gamma AI)



Results & Discussion

The results showed that each AI system excelled in a different dimension. ChatGPT stood out for organisation and reasoning, producing a well-structured plan that balanced nutrition, calories, and practical sequencing of ingredients. Copilot used the greatest number of unique items and demonstrated the strongest waste-reduction behavior, aggressively incorporating foods likely to spoil quickly. Gemini delivered the most consistent calorie logic and used a systematic “risk-based” approach to freshness, classifying items by urgency to guide meal scheduling. Collectively, these differences highlighted an important point: AI meal planning is not one single skill—models may optimise for structure, utilisation, or numeric consistency depending on their tendencies and how the prompt is interpreted.

A key limitation discussed in the presentation is that calorie and nutrition accuracy depends on how well AI handles real food complexity. Meal plans often contain compound ingredients and “hidden” additions (oils, sauces, seasonings), which can be omitted or misestimated, shifting total calories and macronutrients. Research on large language models in meal planning confirms that ingredient decomposition is a major technical bottleneck for reliable nutrition estimates (Kopitar et al., 2025). This is why the team emphasised evaluation criteria beyond “nice-looking menus”, including feasibility and calculation consistency.

Conclusion & Mission Alignment

The team’s broader conclusion was that smart-fridge intelligence can be democratized. While Samsung-style systems integrate cameras and computing inside an appliance, related research on AI-enabled smart fridge architecture shows how computer vision, inventory tracking, and decision-support can work as modular components (Thuc et al., 2025). Building on this idea, the presentation proposed future work toward an “AI Pocket Fridge Assistant”—a phone-based tool that could scan expiration dates (OCR), recognize foods visually, and generate meal plans offline or with low data usage, improving access for low-resource communities. (Figure 2)

Figure 2. AI pocket fridge assistant (Gamma AI)



Finally, the project acknowledged ethical guardrails: AI-generated nutrition guidance can be helpful, but it should be presented transparently and cautiously—especially for medical nutrition contexts. Studies benchmarking AI dietary recommendations in chronic kidney disease show that outputs can vary in safety and accuracy, reinforcing the need for validation and clear boundaries on medical use (Kairat et al., 2025). With these safeguards, the project demonstrates a practical and mission-aligned pathway: using AI to reduce waste, support healthier choices, and advance the common good across borders.

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Is AI-Prompted Engineering for Graduate Nursing Students?

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Introduction

The integration of artificial intelligence (AI) into academic nursing graduate work has transformed how instructional materials are produced, analyzed, and assessed. In graduate nursing education, learners' performance is critical in fostering successful academic excellence (Simms, R.C., 2025).

Purpose

This project explored how graduate nursing faculty analyzed learner performance data and generated individualized instructional materials through strategic AI-prompted engineering, aiming to ensure learners' performance success.

Terms

Traditional Questions

Questions asked directly without help from AI. The questions come from a person's own understanding, curiosity, or confusion.

AI-Assisted Questions

Questions formed by a human but refined, clarified, or expanded with the help of AI.

AI-Prompted Questions

Questions that are generated entirely by AI, often proactively, without a human explicitly asking. AI uses context to suggest questions instructors might want to consider.

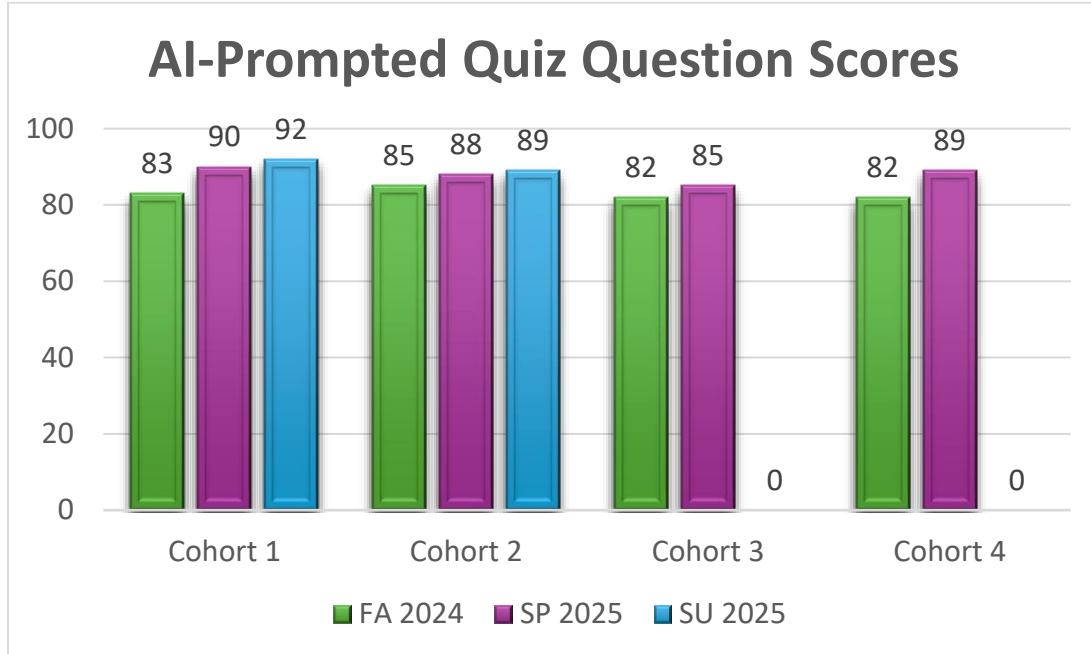
Methods

A sample of three terms of assessment scores from core graduate nursing courses was analyzed and evaluated using Excel spreadsheets and SPSS v29. In 2024, assessment scores were gathered without AI-generated prompting. In 2025, assessment scores were gathered with AI-generated prompting. Faculty compared deidentified aggregate assessment scores with (n=342) and without (n=445) AI-generated prompt engineering to determine if scores had changed, and how the scores may have or may not have changed. The sample compared traditional quiz questions with the AI-assisted and AI-generated prompt quiz questions.

Results

Preliminary independent t-test score findings revealed: Statistical significance with a p-value of 0.004, showing approximately 43% of total assessment submissions illustrating an improvement over 33% overall grade average scores improved with AI-prompted questions. Overall, grades improved 5-8% with AI questions. Faculty reported the ability to identify real-time assessment questions and provide immediate remediation feedback that was not previously flagged through conventional question analysis. Notably, 4% of the overall average scores decreased over the same terms.

Figure 1: Results



Limitations

Limitations include a convenience sample, a limited time frame, one instructor, two courses, and four cohorts at a single University. Inclusion Criteria- Enrolled as an active student in the courses during the entire term. Exclusion Criteria- All students not enrolled, withdrawn, or auditing the courses.

Discussion

While AI-prompted engineering questions offer valuable insights with question pattern recognition, their use must be coupled with faculty judgment and vested learner diligence. AI-prompted engineering questions also cater to individual learning styles- written, pictures, videos, puzzles, and matching. Transparency, communication, AI innovation, and responsive student feedback are essential to learner success (Blomquist, 2025).

Conclusion

AI-prompted engineering in graduate nursing assessments may suggest an improvement in preliminary learner performance in core graduate nursing courses by identifying learner comprehension patterns and learner engagement in the content. However, AI-prompted engineering does not replace learners' overall effort and faculty discernment (Evangelista, 2025). Continued research is necessary to refine best practices.

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Agentic AI for Global Sight: Promoting Mobility for All in Africa, USA, and Beyond

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Introduction

This project sought to design an AI-powered direction system to enhance mobility, safety, and independence for visually impaired individuals. Traditional aids such as canes and guide dogs are limited. However, by integrating computer vision, GPS, sensors, and voice assistance, AI can provide real-time navigation support. More specifically, visually impaired individuals face significant challenges navigating environments due to limitations of traditional mobility aids like white canes and guide dogs (AllAfrica, 2023). This limitation highlights the need for more advanced solutions that can enhance autonomy, safety and confidence for people with visual impairment. Artificial Intelligence (AI) offers a promising solution by providing real-time environmental awareness and voice-guided instructions.

Project Overview

This project aimed to design and implement an AI-powered direction system for visually impaired people, enhancing their independence, safety, and confidence. The system leveraged AI technologies like computer vision, natural language processing, and GPS to provide accurate and user-friendly navigation assistance. Moreover, researchers utilized agentic AI to reveal specific ways that technology can advance project goals and serve the common good from Africa to the USA.

Some specific project objectives included 1) Exploring today's challenges for society and proposing an AI-powered direction system that offers accurate environmental information 2) Integrate voice assistance with object detection for obstacle avoidance, utilizing technologies like YOLO (Ogunleye et al., 2023) 3) Show how agentic AI can help create a prototype for researchers seeking to promote how an AI-powered direction system can enhance mobility, safety, and independence for visually impaired individuals in alignment with assistive navigation technologies (Alam et al., 2024) 4) Use Grok's expert mode (agentic AI) to discover two free tools that have agentic AI capabilities that can be accessible to all individuals in Ghana and then also the USA and 5) Showcase an AI-generated infographic that promotes this AI-powered direction system as well as the researchers' strategies to serve the common good through technology. The AI-generated prototype creation, free agentic AI tools, and infographics (Figure 1 and 2) are given below.

Agentic AI Output: Three Steps for AI-Assisted Prototype Creation

Step 1. System Design

AI tools like simulation software (e.g., Unity or Gazebo) help model integration of computer vision for obstacle detection, GPS for routing, sensors for environmental data, and voice AI for guidance. Researchers define requirements, simulate scenarios, and iterate designs virtually to ensure real-time functionality before hardware prototyping.

Step 2. Prototype Development

Using AI frameworks such as TensorFlow or PyTorch, integrate components into a wearable or app-based system. Code computer vision algorithms for object recognition, fuse sensor data with machine learning for accurate navigation, and add voice assistance via APIs like Google Speech-to-Text. Build a minimum viable prototype on affordable hardware like Raspberry Pi.

Step 3. Testing and Refinement

Deploy the prototype with volunteers in controlled environments. AI analyzes user feedback and performance data to refine algorithms for usability and accuracy. Iterate through machine learning retraining, ensuring affordability and scalability. Finalize for global accessibility, from Africa to the USA, promoting independence for visually impaired individuals.

Two Free Agentic AI Tools

1. Auto-GPT: Free open-source autonomous AI agent on GitHub that uses LLMs to break down tasks, execute actions like web searches or code writing, and iterate independently. Accessible via internet in Ghana and the USA with Python setup.
2. Hugging Face Agents: Free library for building agentic AI systems with transformers; enables tool-using agents for tasks like data analysis. Web-based access worldwide.

Figure 1. AI-created infographic to promote AI navigation to serve the common good (Grok AI)

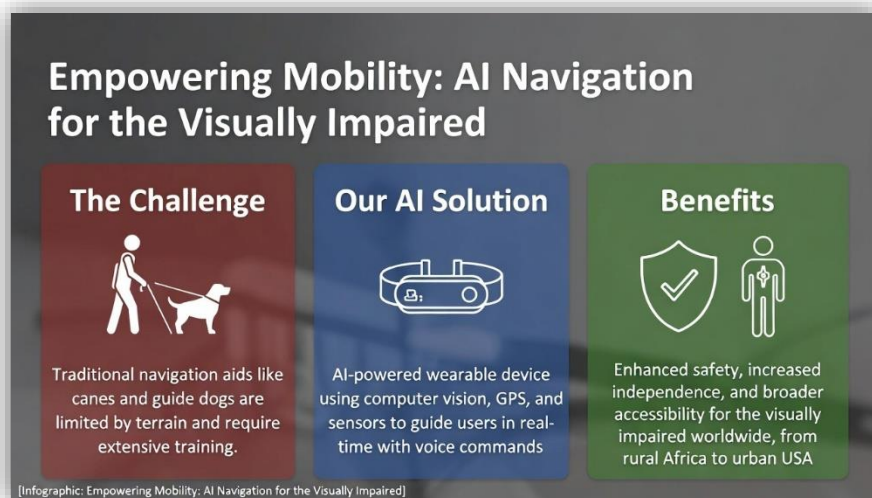
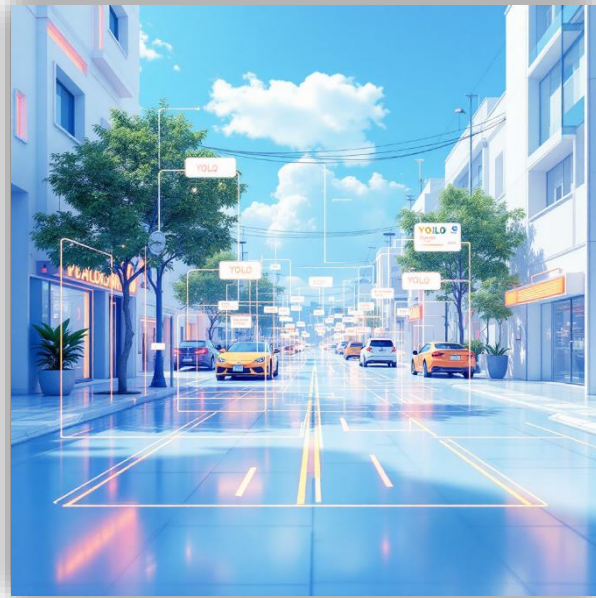


Figure 2. AI-generated representation of AI-powered directional system (Gamma AI)



Conclusion

Agentic AI can revolutionize mobility for visually impaired individuals by autonomously integrating computer vision, GPS, sensors, and voice guidance into navigation systems. Unlike static aids, these proactive agents provide real-time, adaptive support, enhancing safety and independence. Free AI tools allow accessible access. AI-created infographics can promote research ideas and emphasize how AI can serve others, particularly to make a global impact. Essentially, agentic AI serves the common good, strengthening independence and reducing barriers for millions, ultimately advancing technology for societal benefits from Africa, USA, and beyond.

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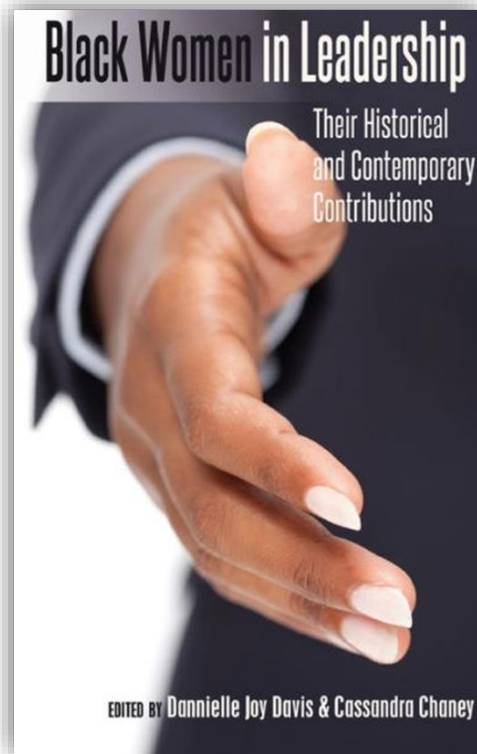
Black Women and AI: Past and Contemporary Perspectives

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Abstract

The accelerated and constantly evolving advancement of AI (artificial intelligence) technology, along with its application to teaching, research, and service has influenced academe exponentially in a relevantly short period of time. Inspired by the book, “Black Women in Leadership: Their Historical and Contemporary Contributions” (2013, Figure 1), a senior faculty member highlights her initial concerns about the ethics and utility of various AI tools. Discussion of the author’s shifting perspectives are complemented by her examples of ethical use of AI application to teaching, learning, and research. Finally, the work summarizes her institution’s approach to AI in 2025 and the supports or tools offered to faculty members to learn it.

Figure 1. Black Women in Leadership: Their Historical and Contemporary Contributions



Introduction

I initially held deep ethical concerns and hesitancy on the use of AI in academic spaces. However, after meeting weekly with professional development groups to learn more about AI and attending virtual AI conferences, I became quite adept at understating the multifaceted uses of AI and discovering ways to apply it to the learning process ethically. Not only did I become a Peer Leader

in AI, teaching and mentoring other faculty nationwide in AI use, but I also included ethical critique of AI as a component of my teaching and scholarship. The following describes how.

Teaching in the Age of AI

In 2025, I found numerous creative ways to incorporate AI into my classroom. For instance, in one class we explored ways that AI was used to promote educational access for people with various disabilities. For this course, one of our featured guests was Tiffany Martin, an AI entrepreneur who develops AI technology for the visually impaired (Figure 2). As a visually impaired person herself, she developed the company, VisioTech, which expands access to the visually impaired using various forms of AI.

Figure 2. Tiffani Martin, CEO of VisioTech, <https://visiotech.co/>



I also created exercises to encourage ethical use of AI. For example, in one exercise, students would form their own definitions of terms using course content. After reviewing their definitions of course content terms, we next would ask “What’s AI’s definition of “XYZ?”” The students enjoyed comparing the human versus the AI definitions. Sometimes AI was accurate, while other times it was grossly incomplete, illustrating to the students both its strengths and weaknesses as a tool. Another way I implemented AI in the classroom is as a Final Project Option, which allowed the use of AI to create a course-related Website or App.

University Responses to AI

In terms of my university’s response to AI, I describe my observations using Bronfenbrenner’s Ecological Systems Theory as a lens (Table 1). The Microsystem level response to AI of faculty members I closely work with has been faculty occasional personal use of AI, but not necessarily ingraining it into their professional lives. Next, there is the Mesosystem level of AI implementation. An example of this includes how our Teaching and Learning Center assisted faculty in creating AI statements to place into syllabi and how they have supported faculty autonomy in terms of if and how AI is used in their individual courses. At the Exosystem level,

learning opportunities our university offers include Workday training options in AI on a regular basis. In addition, Amazon visited our campus and did a workshop on their company’s AI tools.

Table 1. AI Response

My University Community’s 2025 AI Response		
Microsystem Level	Mesosystem Level	Exosystem Level
Faculty individual, personal uses of AI.	Univ. Teaching and Learning Center support faculty AI statements in syllabi.	Various “Workday” training options in AI offered to all university faculty and staff.
	Faculty members establish AI use for individual courses.	AWS (Amazon Web Services) Workshop on company’s AI tools.

Conclusion

My understanding of AI continues to evolve. I have gradually transformed from an AI skeptic to a dedicated AI Ethicist and cautious guide. As it’s reach influences every level of education (K-20), I look forward to observing its multifaceted developments and adaptations to learning, teaching, research, and service to the community.

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Economics Students' Curiosity, AI-Driven Self-Regulated Learning and Learning Performance: A Mediation Model

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Curiosity is a central motivational force in learning, driving individuals to explore, inquire, and engage with new information. Contemporary scholarship distinguishes between interest-type curiosity, which reflects enjoyment-based exploration, and deprivation-type curiosity, which arises from a desire to resolve knowledge gaps (Oudeyer et al., 2021; Whitecross, 2024). In technology-enhanced learning environments, particularly those supported by artificial intelligence (AI), these motivational processes may be amplified through adaptive feedback, personalised scaffolding, and continuous monitoring of learning progress (Acquah et al., 2025). Such affordances align closely with the principles of self-regulated learning (SRL) and have the potential to strengthen students' academic self-efficacy, a well-established predictor of learning performance (Schunk & DiBenedetto, 2022; Liang et al., 2023). Despite this theoretical alignment, empirical evidence explaining how curiosity translates into learning performance through AI-supported SRL and self-efficacy remains limited, especially in economics education. This study addresses this gap by examining the sequential relationships among curiosity, AI-driven SRL, self-efficacy, and learning performance.

Guided by Social Cognitive Theory and Self-Determination Theory, the study conceptualises curiosity as an antecedent of active learning engagement. Interest-type curiosity encourages sustained interaction with learning materials due to intrinsic enjoyment, whereas deprivation-type curiosity motivates focused effort aimed at resolving uncertainty (Tu, 2025). When learners engage with AI-enabled tools, these motivational states are expected to foster SRL behaviours such as planning, monitoring, and reflective evaluation (Rakhmetov et al., 2025). Over time, repeated success in regulating learning activities enhances students' beliefs in their academic capabilities, thereby improving learning performance. This theoretical logic suggests a sequential pathway in which curiosity influences performance through AI-supported SRL and academic self-efficacy (Wang et al., 2025).

To test these assumptions, the study adopted a cross-sectional research design involving a purposive sample of 427 higher-education economics students who had prior exposure to AI-supported learning tasks. Data were collected using a structured questionnaire comprising validated measures of interest-type curiosity, deprivation-type curiosity, AI-driven self-regulated learning, self-efficacy, and perceived learning performance. Responses were analysed using Partial Least Squares Structural Equation Modelling, following established procedures for assessing

reliability, validity, and structural relationships. Bootstrapping techniques were employed to examine direct and indirect effects among the study variables.

The findings indicate that both interest-type and deprivation-type curiosity positively influence students' engagement in AI-driven self-regulated learning as well as their learning performance (Guo & Li, 2025). Deprivation-type curiosity exhibited a stronger association with SRL, suggesting that the motivation to resolve knowledge gaps plays a particularly important role in activating goal-directed regulation when AI tools are available (Akgün, 2022). Interest-type curiosity, however, demonstrated a comparatively stronger relationship with learning performance, reflecting the value of sustained, enjoyment-based engagement in learning tasks (Donnellan, 2022). Self-efficacy emerged as a central mechanism in the model, exerting a strong influence on both self-regulated learning and learning performance (Zheng et al., 2024). Students who believed in their ability to succeed were more likely to engage strategically with AI-supported learning activities and to report higher academic outcomes.

Further analysis confirmed that AI-driven self-regulated learning and self-efficacy jointly mediate the relationship between curiosity and learning performance (Banihashem et al., 2025). Specifically, curiosity was found to enhance learning outcomes indirectly by fostering self-regulated learning behaviours, which strengthened self-efficacy and, in turn, improved performance (Shin, 2024). The presence of this sequential mediation underscores the importance of viewing AI not merely as a technological aid but as a pedagogical resource that shapes motivational and regulatory processes essential for effective learning.

These findings contribute to the growing literature on AI-supported learning by demonstrating that the educational value of AI tools lies in their ability to support learners' self-regulation and confidence development. From a practical perspective, the results suggest that educators should design AI-enhanced learning activities that intentionally scaffold SRL processes, including goal setting, progress monitoring, and reflective evaluation. Instructional strategies that promote curiosity and provide mastery-oriented feedback are also likely to strengthen students' self-efficacy and learning performance. At the institutional level, investments in AI-enabled platforms should be accompanied by pedagogical guidance that helps students use these tools strategically rather than passively.

Despite its contributions, the study is limited by its cross-sectional design and reliance on self-reported data, which constrain causal interpretation and generalisability. Future research could employ longitudinal or experimental designs to examine how curiosity, SRL, and self-efficacy evolve in AI-supported learning environments. Qualitative investigations may also provide deeper insight into students' lived experiences of regulating their learning with AI tools.

In conclusion, this study provides empirical evidence that curiosity serves as a critical motivational foundation for learning performance when supported by AI-driven self-regulated learning and academic self-efficacy. By elucidating the pathways through which curiosity translates into

academic outcomes, the study advances understanding of how AI can be pedagogically integrated to enhance learning in economics education and beyond.

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Assessing Acne Management Products Through Clinical and Consumer Perspectives Using ChatGPT

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Acne management is important for young adults to maintain overall health and confidence. The integration of ChatGPT for dermatological and product insight serves as a tool for young adults to create a tailored and informative skincare routine.

The ChatGPT prompt focuses on creating a skincare management routine for young adults with acne:

Create a skincare routine of five products for an acne prone young adult with oily skin. Use products that are available at Walgreens. For each product, include information regarding its active ingredients (and their function), suggested use, and predicted outcome. In addition, highlight consumer reviews and experience with the product.

The products provided by ChatGPT for analysis included: A cleanser (CeraVe Foaming Facial Cleanser (for Normal to Oily Skin)), an over-the-counter topical retinoid (Differin® Adapalene Gel 0.1%), Neutrogena On-The-Spot® Acne Treatment (2.5% benzoyl peroxide), and two lotions (CeraVe PM Facial Moisturizing Lotion and CeraVe AM Facial Moisturizing Lotion SPF 30 Oil-Free).

Understanding the quality of the product and its function on the skin leads to confidence in understanding what is being applied as well as what it is doing. After ChatGPT was used to provide a regime of products, the following prompt was given to address the question of the function and quality of each product:

Please provide an explanation of what each of the following products will do in terms of the quality of the product as well as the effects on the skin after use. With this, please provide a list of pros and cons for using each specific product in comparison to others as well as providing alternative suggestions.

ChatGPT provided each product with a description detailing what it did for the skin, including key characteristics that were consistent among consumer feedback. It provided a price range- as being affordable was a quality that was sought after. A description of pros and cons were then given for each product, going into depth about details that were found for overall response trends. ChatGPT then described why the product might affect certain individuals in a different way than others based off of demographic or certain ingredients that react in a variety of ways. The last tip that it provided

was a section listing similar products that might be more available, cheaper, stronger, or more geared towards a certain ailment for a more in-depth and personalized regimen. Overall, ChatGPT was able to carefully detail the function of each product in an in-depth way, while still maintaining a straightforward and concise description.

Having access to the chemistry behind a product is helpful for consumers to feel safe and confident in ChatGPT product recommendations. After the initial product recommendations were given, the following prompt was used to define the biochemistry of each product:

Give a detailed explanation of how the following active ingredients function in terms of chemical mechanisms with the skin. Include molecular function within the product and with the skin. Include any sources or biochemistry research papers.

ChatGPT gave a detailed response for each product, outlining product mechanisms, the active ingredients, and their function. Some of the active ingredients in the products overlapped, but ChatGPT was able to state both its function from a dermatological and product formulation perspective. For example, ceramides were an active ingredient in three of the CeraVe products. Ceramides reinforce the lipid bilayer to reduce trans epidermal water loss (TEWL). However, ceramides must be formulated into cleansers and lotions with different technologies since they interact with the skin for varied periods of time. In lotions, time-release emulsion vehicles are used to slowly release the ingredient over time; while in a cleanser, ceramides are encapsulated in micelles in order not to be washed off the skin. ChatGPT explains these differences and their impact between each product in the suggested routine.

Figure 1. Infographic Created by ChatGPT



Next consumer reviews were analyzed using ChatGPT using the following prompt:

What are the overall product reviews and ratings of each of the following products. Are they dermatology recommended? Give me the pros and cons of each and include real reviews of them.

This analysis found that across the five products, review findings show consistently high consumer satisfaction, with differences largely reflecting each product's role, expected side effects, and skin-type suitability rather than overall quality.

The CeraVe Foaming Facial Cleanser received the strongest and most consistent ratings, driven by its gentle, fragrance-free formulation and inclusion of ceramides, niacinamide, and hyaluronic acid. Reviews emphasize reliability, barrier support, and broad tolerability, with negative feedback largely limited to dryness or breakouts in a minority of users. Differin Adapalene Gel shows more variable but generally positive reviews, with users reporting significant long-term acne improvement consistent with its clinical evidence base. Negative feedback primarily reflects early purging and irritation. Neutrogena On-The-Spot Acne Treatment is rated highly for fast, targeted effectiveness, though fabric bleaching and localized irritation are common drawbacks. Finally, CeraVe AM Facial Moisturizing Lotion was well regarded for convenience, despite texture concerns and occasional white cast. Overall, review patterns suggested complementary strengths when these products are used together in a structured regimen.

An analysis of the active ingredients and their safety as well as overall consumer reviews, results, and experience were evaluated for each product using ChatGPT. Considering products from a clinical, scientific, and consumer perspective ensures quality of care for young adults. This provides comprehensive data to create an easily accessible skincare routine that is safe and effective. As a result, ChatGPT can positively impact skin health through acne management.

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Evaluating AI Rendering for the Next Generation of Architects

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Introduction

Throughout history, architectural design has developed from Drawing on Stone, and then using Papers for planning, drawing and rendering, later on with the use of computer Software architectural design had a very quick boost and have become the main source for architects to design buildings, this development has continued and recently with the use of AI, Architecture have had new territory for designing, concept developing, drawing and rendering. For Architects, rendering is a very essential approach to show and imagine the final construction before beginning the work, however, the rendering programs are consuming a lot of time for the designers, which may be replaced with AI rendering in the near future. There have been several different tools that are available in the market for this purpose. The aim of this project is to compare traditional rendering software results with several major rendering engines that are available today, and to make the choice easier for the architects and students to adapt to one of them for their future career.

Comparison & Methods

The project focuses on 3 main areas of architectural design which are (landscape design, exterior design, interior design) with the use of several already existing designs. These designs have been prepared in SketchUP Program, a very useful architectural design software, and then rendered the designs through Corona Engine or Enscape Engine, two most used tools for rendering today. The next step is rendering the same designs with AI tools of (ChatGPT, Gemini, Freepik) and then comparing the results to see which tools give the most realistic rendering result.

Case Studies

1- Landscape Design

The landscape design started with a basic three-dimensional model developed in SketchUp and the model was first rendered manually using Enscape engine. The same model was then rendered using AI-based tools (ChatGPT, Google Gemini, and Freepik) for comparison.

The results of ChatGPT were considered to get the highest overall score, because of its realistic lighting, shadow and material matching. The render preserved its original materials and design details after several improvements in the prompts given for the purpose of rendering. (Image 1)

Image 1. Landscape render by ChatGPT (by researchers)



2- Exterior Design

For the next step, an exterior SketchUp design was prepared using Enscape rendering and then using (ChatGPT, Gemini, and Freepik) for generating an AI rendering. At first, a basic prompt was given to the AI tools and the results were not very promising. After some modifications and detail writing extensions for the prompt, a better render result was achieved after comparing the results (ChatGPT's render). ChatGPT received the highest score because it was easy to use and understood the prompt well, producing balanced colours and realistic results. (Image 2)

Image 2. Exterior render by ChatGPT (by researchers)



3- Interior Design

The same procedure has been followed for an interior design scene of a bedroom shot. The model was first rendered using Corona engine which gave a promising rendering result, and the same view was rendered using the 3 AI tools. ChatGPT again gave excellent lighting realism by combining natural and artificial lights in the scene and also preserved the original textures and materials. (Image 3)

Image 3. Interior render by ChatGPT (by researchers)



Conclusion

After comparing Corona and Enscape renders with AI generated renders, as compared to previous years, AI renderings have developed in a very fast pace. This result can be depended on by architects and architectural students, through preparing a detailed SketchUP design, and then adding the design image into ChatGPT. This gives the most accurate prompt and a very high quality image can be made which reduces time and cost compared to the previous rendering approaches.

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AI for Architecture & Environmental Analysis

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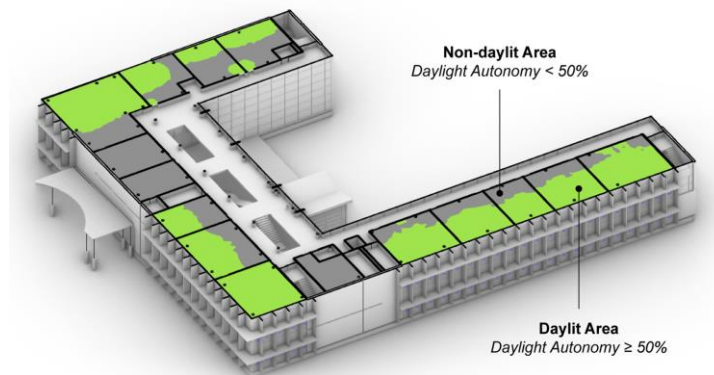
Introduction

This research explores the use of AI “Artificial Intelligence” for the purpose of architectural environment analysis. Recently the use of AI in architectural fields has been improving in a rapid pace, and its use for Environmental analysis is also one of the new features of AI which provides sustainable and energy analysis for the building designs with very fast response compared to the traditional software that were conducting environmental simulations. This research tries to evaluate the accuracy of AI tools for this purpose and discover how architects depend on these data for their designs. The research is a collaborative study of architecture and computer science to examine the architectural use of these tools and the validation of the inserted data in a computer science perspective.

Comparison of Environmental Analysis Tools

In the previous decades, the building environmental analysis software was Energy Plus, OpenStudio, and several other programs. These are very accurate to depend on because they calculate complex physical equations and give correct data according to the given design cases. However, the time consumed to get one analysis is high, so it needs several hours for a building to be completed. Recently, with the use of AI-driven tools, the same analysis could be done within few minutes and hundreds of different options could be studied within the same time period needed for the previous tools. ClimateStudio is one of these tools that provide AI results for building analysis. (Image 1)

Image 1. An example of building environmental analysis. (by ClimateStudio)



Critical Analysis

Following the earlier presentation of the architectural application and the importance of the integrated AI within these applications, it's important to understand what's actually happening behind the AI tools from a technical perspective. The transformation from traditional simulation to AI-driven prediction involves sophisticated machine learning, but the core concept is surprisingly straightforward.

Traditional architectural simulation tools like EnergyPlus and other similar tools such as OpenStudio are well known for their accuracy for simulating heating, cooling and testing the efficiency of a building before building or renovating (U.S. Department of Energy, n.d). However, these tools use complex physics equations from first principle, and they calculate everything step by step. Therefore, they are expensive computationally as a single building simulation and might take hours or even days.

AI contribution changes the traditional ways of simulating buildings by removing the recalculation process by using machine learning that learns the patterns from thousands of previous simulations. These models are trained once and used to predict performance in seconds.

Algorithmic Approaches

One of the main algorithms that power these tools is the Long Short-Term Memory (LSTM). Research on time series modelling has focused on Recurrent Neural Networks (RNN). A study by Ramadan et al. showed that SLTM performs much better than other techniques.

Critical Consideration

There are two fundamental issues that require attention. First is data bias, as most software is trained on western building. Yin Junjia et al. (2024) demonstrates that AI models perform well on the data they were trained on, but the same model may show limited accuracy when applied to different climates. Second, the black-box problem: reasoning and interpretability in these models is still an issue (Meng et al., 2025), these models predict results without explaining the reason and, therefore, professional responsibility and final decision remain human.

Conclusion

The solution is to validate not reject the AI. These models provide speed and accuracy for design exploration; however, the predictions require verification against local expertise for critical decisions by the architects and engineers.

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Artificial Intelligence in the Synthesis of Human Personality

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A research student was inspired by an AI-powered quiz designed to identify a user's ideal study environment. The quiz evaluated multiple AI models based on creativity, emotional insight, and structural design. Each platform received the same questions and the same constraints. The goal was consistency. The results varied widely. Some systems produced shallow suggestions. Others lacked coherence or emotional alignment. Among the tested platforms, ChatGPT+ produced the most effective outcomes and was the highest-performing model. Its responses remained structured without becoming rigid. The system balanced user input with adaptive recommendations and maintained consistency across questions. The results felt intentional rather than generic. This performance shaped the direction of the research and raised deeper questions about how AI interprets human preference.

The early comparison phase revealed a noticeable pattern. When prompts focused on surface-level preferences, most systems performed to acceptable standards. When questions required tone awareness or preference trade-offs, performance dropped. ChatGPT+ demonstrated stronger alignment with how a human might reason through these choices. It adjusted suggestions based on context. It avoided contradictory outputs. It committed to clear answers. These traits pinned it as the most reliable model for further testing and made it suitable for a controlled experiment.

Building on this foundation, the project leaned toward a more focused research question: whether AI can ethically replicate elements of personality traits and preferences using text-based input alone. It focused on decision-making patterns. Using structured personal profile questions, the research examined traits such as color palette preference, comfort with structure, collaboration style, motivation sources, and openness to experimentation. These dimensions shape how people study, communicate, and work. They also serve as consistent markers of personality expression.

The project tested whether AI responses aligned with how real individuals answered the same questions. Human volunteers first provided baseline answers representing their authentic preferences. The AI then received the identical questions with no added context. Responses were compared directly. Each question received a binary score. A match earned one point. A mismatch earned zero. This strict method removed uncertainty and prevented overinterpretation. The approach emphasized accuracy over impression.

As personality complexity increased, a clear pattern emerged. AI as a whole showed moderate success with straightforward preferences. Choices tied to environment, aesthetics, or basic habits aligned more frequently. When questions required emotional nuance, internal reasoning, or value-based judgment, accuracy declined sharply. In the most complex cases, AI failed to match any responses. This pattern formed what the research identifies as a complexity cliff. Performance did not degrade gradually. It collapsed. These findings reframed the project's purpose. The project no longer asks whether AI feels personal. It asks where AI fails. The results showed that AI excels at pattern matching but struggles with integrated personality expression. It lacks access to lived experience, emotional memory, and internal conflict. These elements shape real human decision-making and cannot be reconstructed through text alone.

Despite these limits, the project proved to have meaningful applications. In academic settings, AI informed by documented preferences could support study planning or group coordination. When stress rises or availability drops, an AI assistant could help maintain continuity. In workplace settings, such systems could reduce workflow disruption by reflecting known working styles or communication tendencies. The emphasis remains on support, not substitution. AI does not replace human judgment. It mirrors prior choices within defined boundaries.

Ethical responsibility remains central throughout the project. Personality replication raises concerns about consent, transparency, and misuse. This project treats all personality data as volunteered and controlled. The AI does not infer traits beyond what volunteers provided. The research frames replication as approximation rather than representation. This distinction matters because without clear limits, AI risks misleading users, especially in high-stress environments such as mental health, education, or professional decision-making.

In alignment with Walsh University's mission, this project integrates critical thinking, ethical responsibility, and service to others. The research emphasizes clarity over hype and evidence over assumption. It demonstrates how emerging technology should be evaluated through both performance and principle. By grounding experimentation in values-based education and guided reasoning, the project reflects Walsh University's commitment to forming leaders prepared to serve others through thoughtful innovation and ethical awareness.

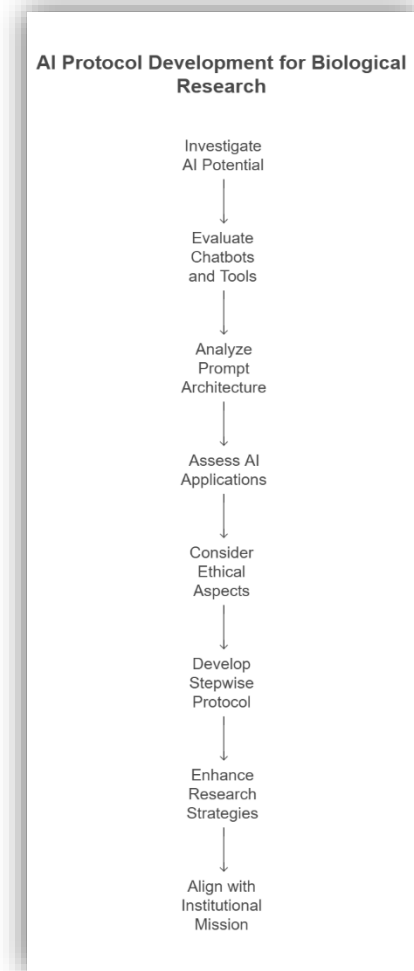
The conclusion that the project delivers is that true personality replication remains beyond current AI capability. As complexity increases, accuracy declines. This reality does not weaken the value of AI. It clarifies its role. Understanding where AI performs well and where it fails protects users and strengthens trust. The research has potential for continued study, wider datasets, while reinforcing a simple truth: human personality remains irreducibly human.

Developing a Revised Framework to Better Utilize AI to Improve the Research Process

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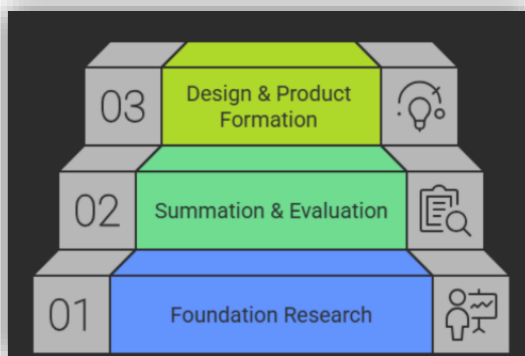
This project, conducted by an undergraduate student researcher, focuses on improving and revising a previously developed AI framework designed to aid in the research process. The original framework, presented in April 2025, was designed to guide those new to research using AI tools on how to use them ethically, and helped establish best practices from the perspective of student researchers, presenting the framework. While helpful and detailed, it included a variety of steps that could have been consolidated to remove redundancy. Additionally, once individuals utilizing the framework became well-versed in AI and the tools available, they would outgrow the need for this guidance. Lastly, the original framework shown in Figure 1 placed a lot of emphasis on the selection of tools, creation of prompt architecture, and devising a desired application to research goals.

Figure 1: Original AI Framework (Napkin AI)



In contrast, the revised framework focuses on the research application by working to utilize AI tools to improve efficiency and research outcomes. Through improving research capabilities and exploration, efficiency in summation and source evaluation, and final product development, the revised framework provides an enhancement of the research process. However, one limitation of the revised framework is that it assumes two main factors. Firstly, the individual utilizing the framework already has established what topic or area of study to explore for their research. Secondly, the individual also has some prior experience with AI and may have preferred tools. The revised framework is shown in Figure 2.

Figure 2. Revised AI Framework (Napkin AI)



Moving on, the revised framework is divided into three main steps or phases and can make use of a variety of tools depending on the goals of the researcher. The framework is broken into these steps to allow for flexibility to match project demands and to allow multiple tasks to be completed as needed. Step 1 is the curation of foundational research, in which tools are used to help improve efficiency in collecting background literature, determining holes in existing research, and determining potential directions of research. In the student researcher’s demonstration, the tool “ResearchRabbit” was selected. This tool was used to show how AI tools could more efficiently collect related material for the researcher. Step 2 of the revised framework is the summation and evaluation of collected materials. This step includes tasks like summarizing material, evaluating material, identifying holes in the literature, and identifying trends. This step allows the researcher to work through large amounts of data and research more quickly, improving overall efficiency. In the demonstration, the student researcher utilized “Notebook LM.” This tool allowed the researcher to quickly summarize and identify trends in the collected works selected for the demonstration. However, it is important for the researcher using tools for summation and evaluation to eventually evaluate their summarized research by hand. AI may not be completely accurate, so this step is just to limit the amount of frivolous evaluation needed and help the researcher determine what research to focus on at that time. Thus, it reduces wasted time used on research that does not match the intended subject matter or is outdated. Step 3 of the revised framework is product development. In this step, AI tools are utilized to increase efficiency in creating a final product. This step includes necessary flexibility as project demands can vary significantly; however, the framework is additionally designed to allow for “plug and play” of AI tools to further meet this need. Some tasks included in this step are graphic creation, improvement of efficiency in writing processes, and presentation creation. For the demonstration, the student researcher selected “Napkin AI.” This tool allowed the researcher to take text and create quality

graphic materials to help build a presentation. Thus, it reduces the time spent finding graphic materials or making them by hand.

Prior to concluding, it is important to note that this framework was designed with “plug and play” in mind. Individual researchers using this revised framework can use any tools they are comfortable with or prefer at any step, and the framework will still provide the intended benefits. Additionally, this flexibility in both tools used and goals of each step allows for the framework to be better applied to a variety of projects and meet more specific goals.

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Beyond the Replication: Modeling and Environmental Effects

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A student researcher, inspired by the ethical project of AI personality replication, chose to expand their focus to the modeling and commands that form the base of prompts. The goal is to understand not only the output of artificial intelligence, but also the deeper processes that shape how responses are generated and how those responses may mirror elements of human personality and decision-making.

Building from earlier work on personality replication, this project shifts attention away from surface-level imitation and toward internal structure. Rather than evaluating whether AI responses sound human, the research examines how prompt creation, system constraints, and modeling influence what the system produces. This approach reframes AI personality modeling as a design problem rather than a behavioral illusion, emphasizing construction over appearance.

By analyzing data from their own research experiments and comparing it to similar research in the field, the student researcher aimed to evaluate both the potential and the limitations of AI personality modeling. These comparisons include experimental prompt trials, structured personality-based prompts, and findings from large-scale generative agent studies. Together, these sources provide a clearer picture of how closely AI can maintain consistency, structure, and tone across repeated interactions, while also revealing where accuracy begins to break down as complexity increases.

Beyond that, the project's goal is to inform attendees of the environmental impact AI has on the environment and propose more efficient ways to both preserve the environment and further develop AI. While discussions of AI often emphasize innovation and capability, this project places equal weight on cost. Training and deploying large-scale models require significant energy, water usage, and infrastructure. These demands raise concerns about long-term scalability, especially as AI use becomes widespread across education, healthcare, and industry.

As society innovates and constructs more technology, the widespread use of AI has become normalized. With this great improvement in everyday life comes great responsibility. The research presents how increasing reliance on AI systems intensifies environmental strain, particularly through data centers, cooling requirements, and continuous inference demand. Promoting environmental stewardship is therefore not separate from technological progress but essential to it. Addressing sustainability directly helps ensure that AI development remains aligned with broader societal values.

Promoting environmental stewardship will further develop trust in these emerging technologies. Trust does not come only from performance. It comes from transparency, accountability, and a willingness to acknowledge limitations. By openly discussing environmental impact and proposing strategies for efficiency, the project encourages a more honest relationship between users and AI systems. This transparency helps prevent overreliance and supports informed adoption.

The project proposes applications in education, wellness, and organizational progression. These applications are framed carefully. The project does not position AI as a replacement for human judgment or interaction. Instead, it explores how AI can function as a structured support system when used within ethical and practical limits.

For students, AI can serve as a supportive tool that helps maintain study habits or facilitates group projects when scheduling conflicts arise. When students are unavailable or overwhelmed, AI systems informed by structured prompts and clear constraints can help preserve continuity. This support can reduce stress, improve coordination, and provide consistency without replacing individual agency or responsibility.

For organizations, it could act as a temporary assistant, helping maintain workflow and reducing disruptions when individuals are unavailable. AI systems guided by well-designed prompts may help maintain structure, document preferences, or reflect established workflows during short-term absences. The emphasis remains on assistance rather than authority, ensuring that final decisions remain human-led.

Moreover, by informing attendees about the environmental hazards and proposing ways to help preserve our environment, we could foster more comfort and trust in using AI. This dual focus on capability and consequence strengthens ethical awareness. The project encourages humans to view AI not as an abstract tool, but as a system embedded in physical infrastructure with real-world costs.

This project demonstrated the integration of critical thinking, ethical responsibility, and service to others, which aligns with Walsh University's mission. The project emphasizes reflection alongside innovation and evaluation alongside enthusiasm. It invites audiences to question assumptions, examine evidence, and consider long-term impact rather than short-term convenience.

Overall, this research explores the balance between innovation and ethics. This balance sits at the center of the project. The research concludes that while AI personality modeling and prompt-based design show meaningful promise, they remain bounded by cognitive limits and environmental realities. Recognizing these boundaries strengthens responsible use and supports a future where technological development remains guided by human values, environmental care, and thoughtful leadership.

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Artificial Intelligence for Food Safety: Strengthening Protection from Farm-to-Table

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Overview

This project showcased the work of two student researchers examining how artificial intelligence (AI), especially agentic AI, strengthen food safety across the entire farm-to-table chain. Our project emphasised a dual focus: (1) industrial food systems, where AI can enhance microbial detection, quality control, and supply-chain monitoring, and (2) household and community environments, where AI can support safer storage and preparation in low-resource settings. We also used South Africa and Lebanon as comparative contexts because both include informal markets and uneven infrastructure, where food-safety risk can be higher and monitoring systems are often fragmented. The regional focus for South Africa (Figure 1) and Lebanon (Figure 2) are shown below.

Figure 1. Informal food market in South Africa (Gamma AI)



Global Food Safety

To begin, the urgency of food safety is well-established. The World Health Organisation estimates that unsafe food contributes to illness for hundreds of millions of people globally each year (World Health Organisation, 2015). Yet conventional food-safety tools—manual inspections and

laboratory testing—are frequently slow, reactive, and limited by cost and staffing. In response, our project introduced agentic AI as a practical evolution of food-safety intelligence: systems that can perceive risk signals (such as temperature, humidity, and contamination indicators), reason about risk in real time, and support timely interventions before small issues become outbreaks. This approach aligns with public-health surveillance principles, where early detection and rapid response are essential for preventing wider harm. For example, surveillance networks such as FoodNet illustrate how systematic monitoring can inform prevention strategies and improve population-level food safety outcomes (Centers for Disease Control and Prevention, 2024).

Figure 2. Informal food market in Lebanon (Gamma AI)



AI to Improve Food Safety

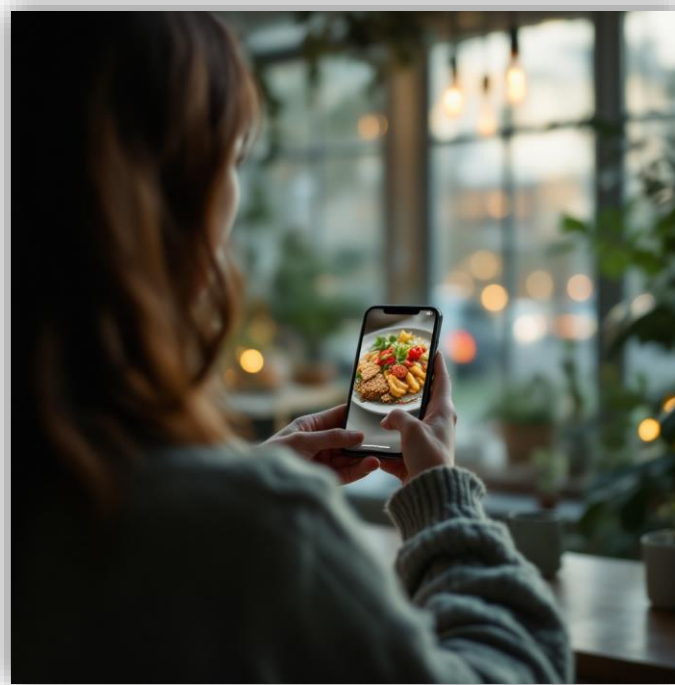
Moving forward, researchers discovered how AI strengthens food safety at the industrial level through faster detection and improved inspection workflows. One major application is AI-assisted microbial detection, where models analyse sensor outputs, spectral patterns, or imaging data to identify contamination risks earlier than traditional processes. Industry commentary highlights biosensor and AI approaches that can reduce time-to-detection dramatically in certain settings, enabling earlier containment and fewer downstream exposures (AgriBusiness Academy, 2025). Researchers used Seaquire Labs as an example of AI-enabled biosensing in aquaculture environments, illustrating how early pathogen detection can prevent full outbreaks and protect both consumers and producers (AgriBusiness Academy, 2025). In parallel, computer-vision systems can support quality assurance by detecting defects or abnormalities in packaging and products that may be missed through manual review. This aligns with industry efforts to expand responsible AI adoption and improve operational decision-making at scale, as seen in Nestlé’s

participation in collaborative initiatives focused on enterprise AI readiness and capability-building (Nestlé, 2025).

Supply-chain Monitoring and Low-resource Community Interventions

Lastly, this project explored farm-to-table risk reduction through supply-chain monitoring and low-resource community interventions. Supply chains are vulnerable to temperature excursions, humidity shifts, and time delays that accelerate spoilage and increase contamination risk. AI paired with connected sensors can flag anomalies during transportation and storage, supporting earlier interventions and reducing waste (IONI, 2025). However, our work emphasised that the highest-impact opportunities in countries like South Africa and Lebanon are often found beyond large factories— particularly in township markets, informal vendors, and households that may lack reliable refrigeration. In these contexts, AI does not need to be expensive or embedded in premium appliances. Practical options include smartphone-based guidance (Figure 3), simple inventory tracking, food-handling chatbots, and localised alert systems developed through government–NGO partnerships (IONI, 2025). By shifting from reactive responses to preventive guidance— especially where formal inspection capacity is limited—AI can support food security while reducing preventable illnesses (World Health Organisation, 2015).

Figure 3. AI for detecting food spoilage (Gamma AI)



Conclusion

Across all areas, our project emphasised that AI can increase speed, consistency, and coverage of food-safety protections, while also reducing waste and improving trust in food systems (Centers for Disease Control and Prevention, 2024; IONI, 2025). At the same time, we acknowledged ethical and practical constraints: privacy risks when monitoring environments, accountability when automated alerts influence decisions, and inequity if advanced solutions remain concentrated

in high-income regions. The most responsible path forward is human-in-the-loop deployment, transparent validation against trusted standards, and deliberate design for low-resource feasibility. Overall, the project argues that AI—implemented thoughtfully—can strengthen public health protection from farm to table while advancing more resilient and equitable food systems.

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Enhancing Actuarial Science Education and Practice Through Artificial Intelligence

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Introduction

This project examines how artificial intelligence (AI) can enhance actuarial science education and professional practice when applied selectively, transparently, and with appropriate human oversight. Conducted through a cross-continental collaboration between Walsh University in the United States of America and the University of the Witwatersrand in South Africa, the study evaluates both generative and agentic AI systems to determine their effectiveness, limitations, and potential contributions to the common good beyond borders (Figure 1).

Figure 1. AI innovation unites universities beyond borders (Gamma AI)



The Impact of AI on Actuarial Science

Artificial intelligence is increasingly reshaping actuarial science by extending traditional statistical techniques through machine learning, natural language processing, and automated reasoning. While actuarial work has historically relied on structured models and historical data, AI introduces the ability to process large datasets, identify non-linear patterns, and rapidly evaluate complex scenarios. When used responsibly, these capabilities can enhance actuarial learning, improve professional efficiency, and strengthen transparency within financial systems.

Research Design

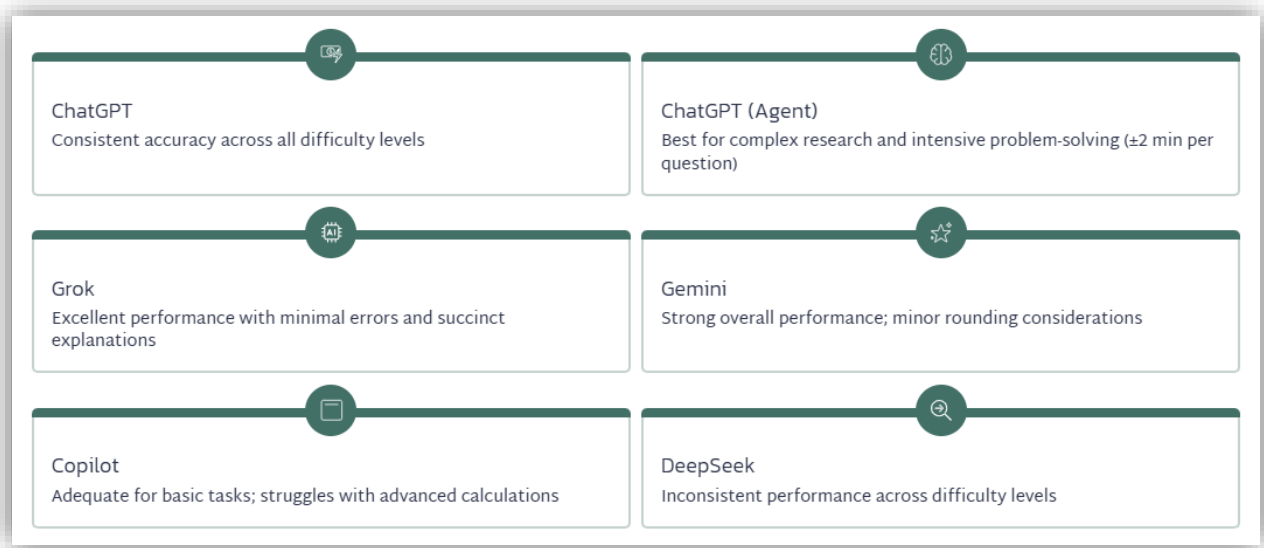
A central focus of this research was a structured comparison of leading AI platforms—including ChatGPT, Gemini, Copilot, DeepSeek, and selected agentic AI systems—across actuarial tasks of increasing complexity. The study employed a three-level testing framework. Basic-level tasks assessed foundational actuarial concepts and simple calculations. Intermediate-level tasks required multi-step reasoning, precision, and correct handling of actuarial tables. Advanced-level tasks demanded intensive problem-solving, often involving code generation and high-stakes numerical accuracy.

Results & Discussion

The findings revealed that AI effectiveness varied significantly across platforms and AI types, with only a subset demonstrating consistent actuarial reliability (Figure 2.) Generative AI systems, particularly ChatGPT and Gemini, performed strongly at basic and intermediate levels by providing accurate calculations, clear explanations, and structured reasoning. These tools proved especially valuable for educational use, where students could compare AI-generated solutions with their own work to reinforce understanding. However, even strong performers occasionally exhibited minor rounding deviations, highlighting the importance of actuarial precision.

Agentic AI systems demonstrated strengths in advanced tasks requiring extended reasoning, research capability, and autonomous execution of complex workflows. ChatGPT’s agentic functionality and Grok achieved high accuracy in advanced scenarios, though at the cost of increased response time. This latency trade-off is an important practical consideration in professional settings. Overall, the results underscored that agentic AI is better suited for complex, research-intensive tasks, while generative AI excels as an immediate, interactive learning aid. Platforms such as Copilot and DeepSeek were found to be inconsistent, particularly at advanced levels, where premature rounding and numerical instability rendered them unsuitable for high-precision actuarial work as described in Figure 2.

Figure 2. Comparative analysis of AI platforms



Beyond Education: AI for Actuarial Practice

Beyond education, the study examined how AI supports actuarial practice, especially in fraud detection and risk management. Machine learning models enhance predictive accuracy by identifying anomalies and hidden relationships within claims data. Natural Language Processing (NLP) assists in detecting suspicious language in financial communications, while neural networks contribute to identifying manipulated records and fraudulent activity (Boulieris et al., 2024; Elly et al., 2025). These applications reduce fraudulent claims, protect policyholders, and strengthen trust in insurance systems.

AI also advances the common good by promoting fairness, accountability, and transparency. Explainable AI allows actuaries to justify pricing and risk classifications to regulators and stakeholders, while also helping identify and mitigate bias in underwriting models. Malali (2025) emphasizes AI's role in collaborative actuarial judgment and solvency management, and Gangani (2024) highlights its contribution to improved fraud prevention and predictive performance. When implemented ethically, AI reduces systemic inefficiencies and supports more equitable financial outcomes.

Despite its benefits, AI introduces ethical challenges related to data privacy, bias, transparency, and overreliance on automation. This research reinforces that AI must function as a complement—not a replacement—to actuarial expertise. Human judgment remains essential to validate outputs, interpret results, and ensure ethical application. Integrating AI literacy into actuarial education equips future professionals to engage critically with these technologies.

Conclusion

Overall, this study demonstrates that artificial intelligence can significantly enhance actuarial education and professional practice when applied selectively and responsibly. By clearly distinguishing between generative and agentic AI, grounding evaluation in precision and reliability, and fostering international collaboration, this project illustrates how AI innovation can serve the common good across borders while strengthening actuarial standards worldwide.

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Democratizing AI: Running Large Language Models on Raspberry Pi

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Abstract

The Raspberry Pi has evolved from a hobbyist's tool into a formidable platform for edge artificial intelligence. This presentation explores the practicality and potential of using Raspberry Pi devices as accessible laboratories for AI experimentation, education, and real-world deployment. We will delve into the hardware capabilities, optimized software frameworks, and a step-by-step demonstration of running local large language models (LLMs) using Ollama. By highlighting practical applications in healthcare, agriculture, and cybersecurity, we underscore the significance of privacy-preserving local inference. The presentation will conclude by emphasizing the role of Raspberry Pi in bridging the gap between AI theory and practice, fostering a new wave of innovation and democratizing access to powerful AI technologies.

Introduction: The New Frontier of AI

The discourse surrounding artificial intelligence is often dominated by large-scale, cloud-based models that require immense computational resources. However, a new frontier is emerging at the edge, where AI is becoming more personal, private, and accessible. The Raspberry Pi, a low-cost, credit-card-sized computer, is at the forefront of this movement. Its affordability, portability, and robust community support make it an ideal candidate for democratizing AI and bringing its power to a wider audience. This presentation will demonstrate that running sophisticated large language models on these small devices is not just a novelty, but a practical and impactful endeavor.

Figure 1: The vision of a decentralized and accessible AI future



The Raspberry Pi as an Edge AI Platform

The Raspberry Pi 5, with its quad-core ARM Cortex-A76 processor, provides a surprising amount of power in a small and energy-efficient package. While not a replacement for high-end GPUs, it is more than capable of running optimized AI models for a variety of tasks. The true power of the Raspberry Pi lies in its versatility and accessibility, making it a perfect platform for learning, experimentation, and deployment of edge AI solutions.

Table 1: Key hardware specifications of the Raspberry Pi 5.

Hardware Specifications

Feature	Specification
Processor	Broadcom BCM2712 2.4GHz quad-core 64-bit Arm Cortex-A76 CPU
Memory	4GB or 8GB LPDDR4X-4267 SDRAM
Connectivity	Gigabit Ethernet, Dual-band 802.11ac Wi-Fi, Bluetooth 5.0
Power	5V/5A DC power via USB-C

The Software Ecosystem

A rich ecosystem of software frameworks has been optimized to run on the Raspberry Pi, enabling the deployment of lightweight AI models. These frameworks are crucial for bridging the gap between powerful AI models and resource-constrained edge devices.

- **TensorFlow Lite:** A lightweight version of Google’s popular machine learning framework, designed for mobile and embedded devices.
- **ONNX Runtime:** A cross-platform inference engine that supports models from various frameworks, including PyTorch and TensorFlow.
- **PyTorch Mobile:** A runtime that allows for the deployment of PyTorch models on mobile and edge devices.
- **Ollama:** An open-source tool that simplifies the process of running LLMs locally, making it incredibly easy to get started on the Raspberry Pi.

Figure 2: Ollama simplifies local LLM deployment



Demonstration: Running an LLM with Ollama

This section provides a step-by-step walkthrough of setting up and running a local LLM on a Raspberry Pi using Ollama. The process is surprisingly straightforward, opening the door for developers and enthusiasts of all skill levels.

Installation

The first step is to install Ollama on the Raspberry Pi. This can be done with a single command, which downloads and sets up the necessary software.

Figure 3: The simple installation process of Ollama

```
Calculating upgrade... Done
0 upgraded, 0 newly installed, 0 to remove and 0 not upgraded.
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
python3-requests is already the newest version (2.28.1-dfsg-1).
python3-requests set to manually installed.
0 upgraded, 0 newly installed, 0 to remove and 0 not upgraded.
pi@raspberrypi:~$ curl -fsSL https://ollama.ai/install.sh | sh
>>> Installing ollama to /usr/local
>>> Downloading Linux arm64 bundle
##### 100.0%
>>> Creating ollama user...
>>> Adding ollama user to render group...
>>> Adding ollama user to video group...
>>> Adding current user to ollama group...
>>> Creating ollama systemd service...
>>> Enabling and starting ollama service...
Created symlink /etc/systemd/system/default.target.wants/ollama.service -> /etc/systemd/system/ollama.service
>>> The ollama API is now available at 127.0.0.1:11434.
>>> Install complete. Run "ollama" from the command line.
WARNING: No NVIDIA/AMD GPU detected. Ollama will run in CPU-only mode.
pi@raspberrypi:~$ ollama --version
ollama version is 0.9.0
pi@raspberrypi:~$
```

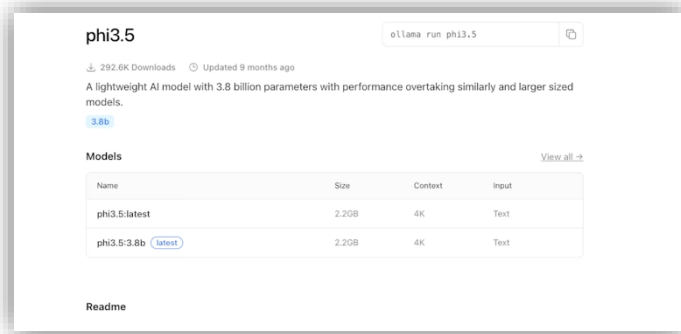
Running a Model

Once Ollama is installed, you can run a variety of open-source LLMs. In this example, we use Microsoft's Phi-3.5, a lightweight yet powerful model.

Figure 4: Running the Phi-3.5 model for the first time

```
pi@raspberrypi:~$ ollama --version
ollama version is 0.9.0
pi@raspberrypi:~$ ollama pull phi3.5
pulling manifest
pulling b5374915da53: 100% 2.2 GB
pulling c6989cc01584: 100% 149 B
pulling c5f9f560a704: 100% 1.1 MB
pulling 45ac4c662a77: 100% 60 B
pulling 0611867ea67b: 100% 409 B
verifying sha256 digest
writing manifest
success
pi@raspberrypi:~$ ollama list
NAME      ID          SIZE   MODIFIED
phi3.5:latest  61819fb370a3 2.2 GB  4 minutes ago
pi@raspberrypi:~$ ollama run phi3.5
>>> What is the tallest mountain in the world?
The tallest mountain in the world, when measured from sea level to its summit, is Mount Everest. Located in the Mahalangur Himalayas in Central Nepal, it reaches an astonishing height of approximately 8,848 meters (29,029 feet) above sea level according to official surveys by China and Nepal as recognized by Guinness World Records before its latest re-measurement. Mount Everest attracts climbers from around the world who attempt various routes to reach its peak yearly during specific season windows—usually May through October, when conditions are more stable for safe ascents. The mountain's inferiority in height is often overshadowed by extreme challenges and risks associated with high-altitude mountaineering expeditions on Everest.
>>> Send a message (/? for help)
```

Figure 5. The Phi-3.5 model is a lightweight powerhouse



Programmatic Interaction

To build applications on top of the local LLM, we can interact with it programmatically. The following Python script demonstrates how to send a prompt to the model and receive a response.

Figure 6: A simple Python script to interact with the local LLM

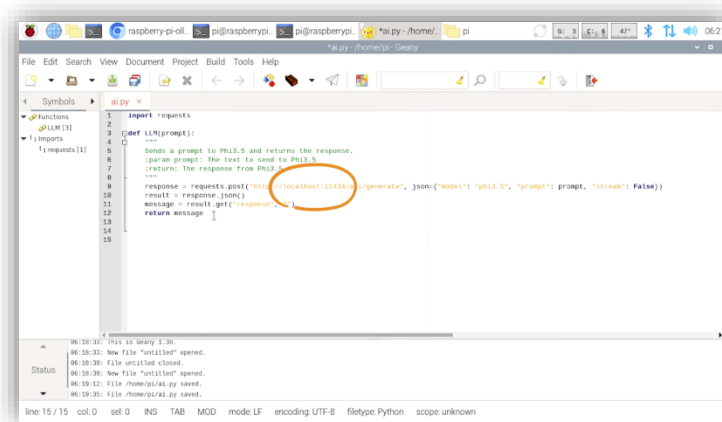
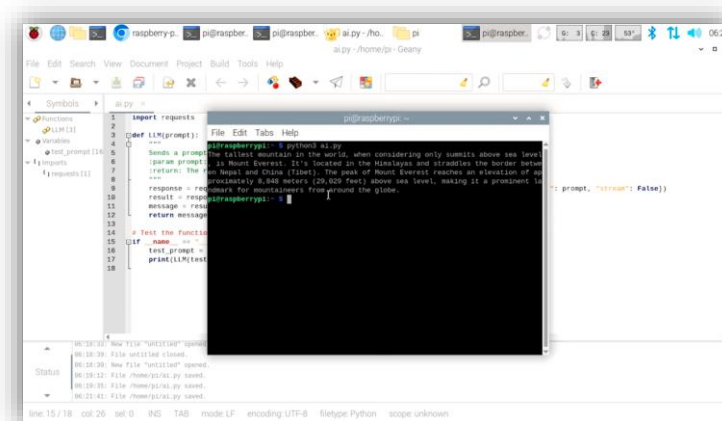


Figure 7. Testing the script from the command line

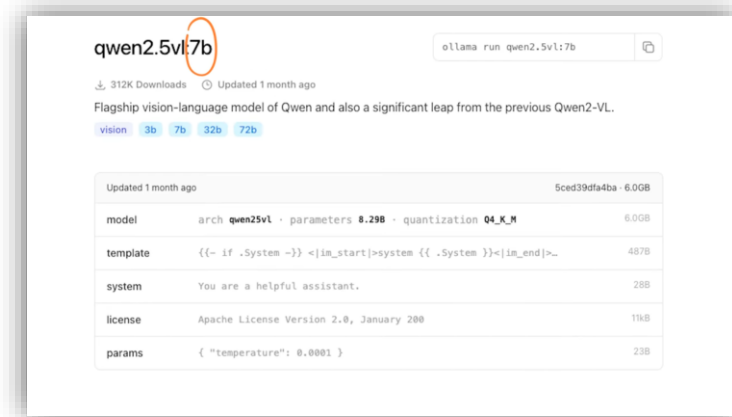


Practical Applications and Use Cases

The ability to run LLMs locally on a Raspberry Pi opens up a world of possibilities for real-world applications where privacy, cost, and low latency are critical.

- **Healthcare Monitoring:** Analyze sensor data locally to monitor patients' health without sending sensitive data to the cloud.
- **Precision Agriculture:** Process data from soil sensors and drones to optimize crop yields.
- **Cybersecurity:** Deploy local intrusion detection systems that can operate without an internet connection.
- **Smart Home Automation:** Create truly private and responsive smart home assistants.

Figure 8: Vision models like Qwen can also be run locally for image-based tasks



AI for Education and Innovation

The accessibility of the Raspberry Pi makes it an invaluable tool for AI education. Students can gain hands-on experience with model deployment, optimization, and the ethical considerations of AI. This practical experience is crucial for bridging the gap between theoretical knowledge and real-world application. Furthermore, the low barrier to entry fosters a culture of innovation, empowering individuals to create novel AI solutions.

Figure 9: Understanding the landscape of available models is key to selecting the right tool for the job

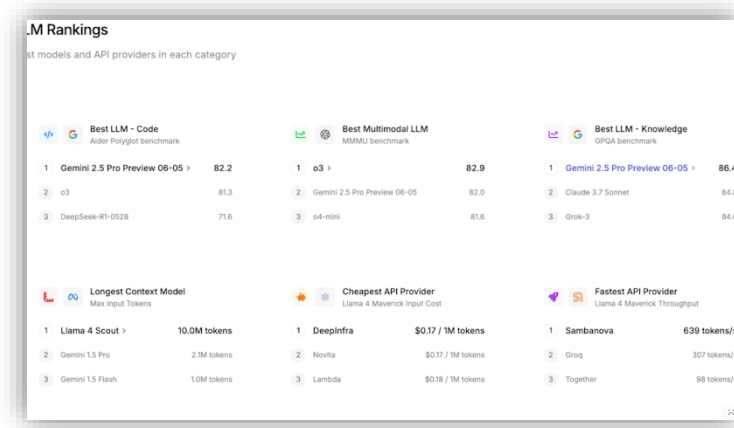
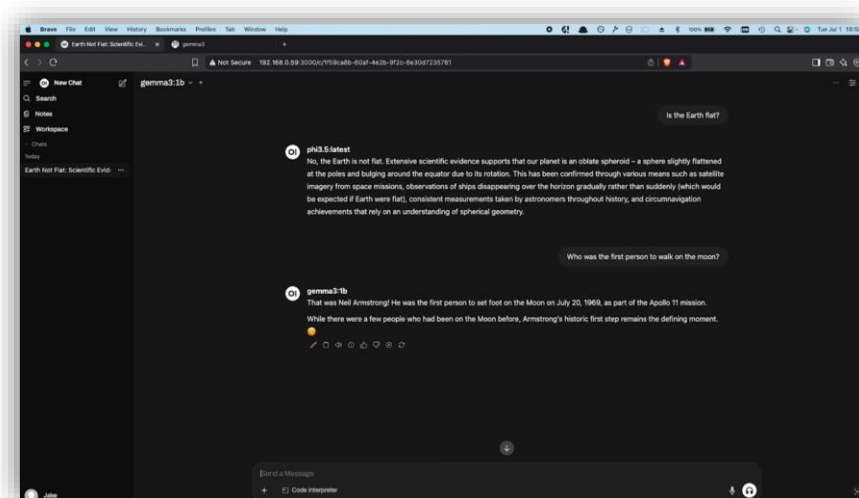


Figure 10: A simple chat interface demonstrates the power of a locally running LLM



Managing and Scaling Local LLMs

As the use of local LLMs grows, so does the need for tools to manage and scale them. LiteLLM is an excellent example of a tool that provides a unified interface for interacting with various LLMs, making it easier to switch between models and manage them effectively.

Figure 11: The LiteLLM dashboard provides a centralized view of available models

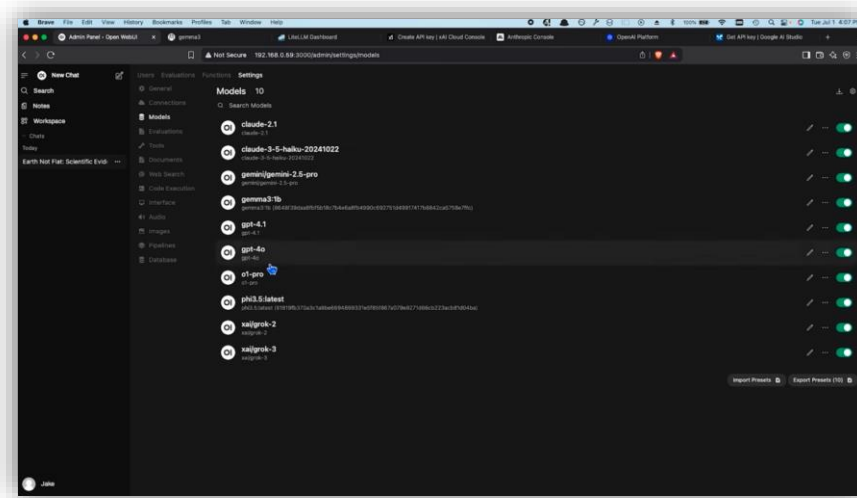
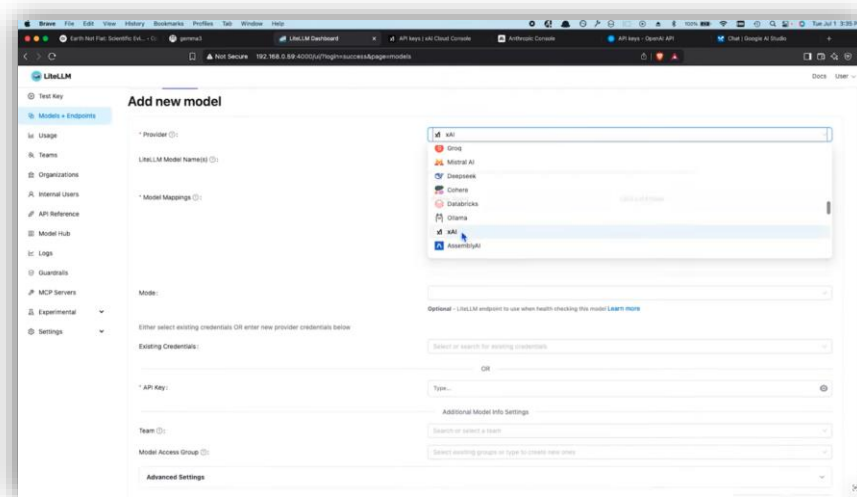


Figure 12: Adding new models to the local environment is a straightforward process



Conclusion: The Future is at the Edge

The ability to run powerful large language models on the Raspberry Pi marks a significant step forward in the democratization of AI. This presentation has demonstrated the practicality and potential of this approach, from the underlying hardware and software to real-world applications and educational benefits. The future of AI is not just in the cloud; it is at the edge, in our homes, schools, and businesses. The Raspberry Pi is a key enabler of this future, empowering a new generation of innovators to build a more accessible, private, and decentralized AI ecosystem.

Figure 13: The freedom to innovate and create with accessible AI



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Modelling the Nexus between AI Literacy and Problem Solving Skills among University Students in Ghana

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Introduction

The rapid integration of AI into education highlights the importance of AI literacy, the knowledge, attitudes, and skills needed to understand and use AI responsibly, for student learning (Salifu et al., 2025). AI literacy encompasses affective, cognitive, behavioral, and ethical dimensions (Arkorful et al., (2025). Prior work suggests that hands-on AI experiences support higher-order thinking and problem-solving in learners. However, the relationship between AI literacy and fundamental problem-solving ability remains underexplored, especially in the Ghanaian context. This study investigates how multiple AI literacy facets relate to university students' problem-solving skills, testing whether stronger AI application use, ethical understanding, and commitment to AI learning predict better problem-solving.

Research Methods

A quantitative survey was administered to 543 undergraduates at the University of Cape Coast. We adopted a simple random sampling approach and used validated instruments. AI literacy was measured along eight dimensions (intrinsic motivation, self-efficacy, confidence, collaboration, ethics, knowledge, application, and behavioral commitment) based on Ng et al. (2024). Problem-solving skills were assessed with a 9-item scale adapted from Hidayat et al. (2023). Responses were on a 5-point Likert scale. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to estimate the direct effects of each AI literacy facet on problem-solving outcomes.

Results

The PLS-SEM model explained 53.9% of the variance in problem-solving skills ($R^2=0.539$; Adjusted $R^2=0.533$). Consistent with hypotheses, AI Application, AI Ethics, and Behavioral Commitment emerged as the strongest positive predictors of problem-solving ($\beta=0.246, 0.262, \text{ and } 0.321$, respectively; all $p<0.001$). In other words, students who actively apply AI tools in learning, who understand AI ethical principles, and who are committed to engaging with AI tasks tend to demonstrate higher problem-solving ability. By contrast, Collaboration showed a small negative path ($\beta=-0.078, p=0.038$), and Confidence, Intrinsic Motivation, and Knowledge/Understanding exhibited non-significant effects ($p>0.15$). These findings indicate that, in this sample, practical AI usage and ethical engagement were key levers for problem-solving, whereas simply feeling confident or motivated about AI (without application) did not predict problem-solving performance.

The results have clear implications for education and policy. They suggest that AI literacy programs should emphasize hands-on AI experience, ethical reasoning, and sustained engagement to effectively boost students' cognitive skills. Instructors and curriculum developers might prioritize projects and instruction that integrate AI tools for real-world problem solving and explicitly teach AI ethics. Policymakers should support resources and training that build students' commitment and competence in AI use. Such initiatives align with calls to incorporate the full spectrum of AI literacy dimensions into learning curricula. By focusing on the facets that drive problem-solving – especially application and ethical use, educators can better prepare students to leverage AI in solving complex challenges.

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