UNIVERSITY OF EDUCATION, WINNEBA

FACTORS INFLUENCING PRE-SERVICE INTEGRATED SCIENCE TEACHERS' ACCEPTANCE AND USE OF GENERATIVE AI TOOLS FOR LEARNING AT UNIVERSITY OF EDUCATION, WINNEBA

FADILA UTHMAN
(8241180002)

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DEPARTMENT OF INTEGRATED SCIENCE EDUCATION
FACULTY OF SCIENCE EDUCATION
UNIVERSITY OF EDUCATION, WINNEBA

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DECLARATION

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I, **FADILA UTHMAN**, declare that this thesis, except quotations and references contained in published works which have all been identified and duly acknowledged, is entirely my original work, and it has not been submitted, either in part or whole, for another degree elsewhere.

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SUPERVISOR: PROF. CHARLES KWESI KOOMSON

SIGNATURE:………………….………… DATE: …………………………………

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SUPERVISOR: DR. ISAAC KWASI ASANTE

SIGNATURE:………………….………… DATE: …………………………………

DEDICATION

Dedicated to my parents, Mr. Uthman Abdullah Alhaji Tanko, and Mrs. Salifa Moro, and my siblings, Ramatu, Fadilu Rahman, Amira, Ridwana, Surraiyyat, Abidat, Sualahudeen, Abdul-Rahman Sudais, Abdul-Jabbar Mukkarram, Hawawu, Salamatu, and Bahjat Uthman.

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ABSTRACT

Generative Artificial Intelligence (Gen AI) tools such as ChatGPT and Google Bard are increasingly transforming higher education worldwide. Their ability to support personalised learning, generate quick information, and enhance students' academic productivity by simplifying complex tasks has drawn attention to their adoption within teacher education. Despite these opportunities, limited knowledge exists on the pre-service integrated science teachers in the use of generative AI tools in Ghana. This study therefore examined factors influencing pre-service integrated science teachers' acceptance and use of generative AI tools in learning at the University of Education, Winneba. Adopting a descriptive survey design, the study collected quantitative data from 300 pre-service integrated science teachers across levels 100 to 400. Descriptive statistics (frequencies, percentages, means, and standard deviations), reliability tests (McDonald's Omega), and inferential statistics were used to analyse the quantitative data. The findings showed that 74% of the pre-service integrated science teachers demonstrated a strong behavioural intention to adopt generative AI tools, with an overall mean score of (Mean=3.67±1.03) on intention. However, only 49.3% reported frequent use. The results further indicated that performance expectancy (Mean=3.90±1.13), effort expectancy (Mean=3.70±0.98), hedonic motivation (Mean=3.73±1.02), and social influence (Mean=3.36±0.92) significantly predicted 74% variation in behavioural intention. Ethical concerns were moderately expressed with an overall mean (Mean=3.01±0.81), however, pre-service integrated science teachers worried about whether using generative AI to complete their work was morally acceptable (Mean=3.21±1.12), plagiarism (Mean=3.00±1.06), misinformation (Mean=3.18±1.11), and privacy breach (Mean=3.10±1.14). Pre-service integrated science teachers' mitigation strategies included integrating digital ethics into teacher training programme (Mean=3.84±1.21) and creating and sharing clear policies on how to ethically use AI tools (Mean= 3.80±1.18) among others. The study concludes that while generative AI tools hold strong potential to enhance integrated science learning, their adoption is constrained by ethical dilemmas and absence of institutional guidelines. It is recommended that the University of Education, Winneba, and the Faculty of Science Education should develop clear policies, integrate ethical AI into teacher training curricula, and strengthen digital infrastructure to promote responsible and effective use.

CHAPTER ONE

INTRODUCTION

1.0 Overview

This chapter discusses the background of the study, the statement of the problem, the purpose of the study, the specific objectives, research questions, significance of the study, delimitations, limitations, and the organisation of the study.

1.1 Background to the study

Generative Artificial Intelligence (AI) refers to AI systems such as ChatGPT, Google Bard, and Perplexity, which can generate new content, such as text, images, or educational materials, and they are rapidly becoming the go-to resource for generating content for different fields of endeavour (Banh & Strobel, 2023). Globally, AI has become a defining technology of the Fourth Industrial Revolution (4IR), a period characterised by the fusion of digital, biological, and physical systems, which are transforming industries, economies, and societies (Ibegbulam et al., 2023). The rapid advancement of this technology has significantly impacted various sectors, including the educational sector (Raja & Nagasubramani, 2018), particularly science education (Goksel & Bozkurt, 2019). In science education, AI-driven technologies are reshaping teaching and learning methodologies by providing data-driven insights, automating administrative tasks, and facilitating personalised learning (Luckin et al., 2016). Countries including the United States, China, and the United Kingdom have integrated AI into their educational systems, leveraging on the technology to support both teachers and learners in learning processes (Selwyn, 2019). AI-powered tools are being used to analyse students' performance, predict learning difficulties, and create adaptive learning platforms that cater for individual students' needs (Holmes et al., 2021).

Generative AI is gaining prominence in science education as students use it for assignments and lab reports (Hsu & Ching, 2023). The technology can create dynamic and interactive learning materials for diverse student needs (Blank et al., 2023). AI-generated simulations and visualisations is assisting students gain a better understanding of complex scientific concepts, and provides instant feedback through personalised tutoring (Davis, 2024). Additionally, Generative AI is assisting educators in designing effective lesson plans and assessments by analysing educational data to identify patterns and insights (Alali et al., 2024).

In Ghanaian education-based universities like the University of Education, Winneba, pre-service teachers including integrated science teachers, as with many other students, are becoming increasingly aware of the existence and potential applications of Generative AI for their academic work (Adjei et al., 2025). However, their awareness levels vary, with some having a deep understanding of how AI functions, while others have limited knowledge of its capabilities and limitations (Hsu & Ching, 2023). Despite its potential, many pre-service integrated science teachers are yet to fully grasp how to use these tools effectively and responsibly in their learning (Alali et al., 2024).

Analysing laboratory reports and assignments of pre-service-integrated science teachers at the University of Education-Winneba revealed that most students used AI tools to write their reports and assignments. The responses obtained from the AI tools used by these students generally provide concise answers to the questions asked but failed to acknowledge the sources of the information given which defies academic integrity (Hsu & Ching, 2023). The effective teaching of integrated science requires a deep understanding of various scientific disciplines and the ability to convey complex ideas in a straightforward manner. Generative AI tools can support pre-service integrated science teachers by providing innovative tools and resources that enhances their learning skills and content knowledge (Nyaaba et al., 2024). Baidoo-Anu and Ansah (2023) posited that, Generative AI improves learning experiences, accessibility to quality educational resources, and foster a personalised learning environment, adaptable to student's learning needs and preferences. Generative AI has been widely used by students and other researchers, especially in the literature review, this has proven to have given accurate information (Batista & Carnaz). However, generates wrong references which has stained the work of some scholars (Wecks et al., 2024). To this end using generative AI for academic purposes should be done cautiously. Because, according to Maphoto et al (2024), Generative AI though beneficial, poses several challenges which hinder the effective integration into science learning. One major issue is the lack of proper training on using these tools ethically and effectively (Liu et al., 2021). Many students struggle with distinguishing between AI-generated content and properly referenced academic literature, leading to potential misinformation or violations of academic integrity policies (Davis, 2024). Moreover, some pre-service integrated science teachers face technical barriers, including limited access to AI tools, inadequate digital literacy skills, and concerns about AI bias and reliability (Hsu & Ching, 2023).

Beyond these challenges, Generative AI has the potential to enhance students' performance in integrated science by providing personalised learning experiences, instant feedback, and interactive simulations that aid concept comprehension (Baidoo-Anu & Ennu, 2024). AI-powered simulations and visualisations help students grasp complex scientific ideas, making learning more engaging and effective (Blank et al., 2023). Additionally, AI can support pre-service integrated science teachers in developing critical thinking and problem-solving skills by enabling them to analyse scientific data, generate hypotheses, and refine their understanding of integrated science concepts (Davis, 2024). While there are challenges to address, the opportunities presented by generative AI in science education are immense (Liu et al., 2021). For pre-service integrated science teachers, generative AI integration can enhance their willingness to adopt generative AI tools for learning integrated science innovatively and impactfully (Ramnarain et al., 2024). Taking into considerations both ethical concerns and its mitigation measures, which makes the integration more effective and ethical. The focus of this study was to examine the factors influencing pre-service integrated science teachers' acceptance and use of generative AI tools for learning.

1.2 Statement of the Problem

Integrated science learning presents challenges for pre-service teachers, particularly in grasping complex scientific concepts, applying problem-solving skills, and engaging with content effectively (Usman Haider, 2024). The rapid advancement of generative AI tools in education presents new opportunities for enhancing learning experiences, particularly in science education (Nyaaba et al., 2024). These tools offer personalised learning, instant feedback, and interactive content generation, which could help students grasp complex scientific concepts more effectively (Zhang et al., 2021). However, traditional teaching approaches often fail to meet individual learning needs, making it challenging for pre-service integrated science teachers to develop critical problem-solving skills (Dziuban et al., 2018). The adoption of AI-driven technologies could bridge this gap by providing adaptive learning experiences tailored to students' needs.

Despite the potential benefits of generative AI in science education, the willingness of pre-service integrated science teachers to accept and use these tools remains uncertain (Baidoo-Anu & Ansah, 2023). Limited research has explored the factors that influence the acceptance and use of AI in learning. Key concerns such as awareness, challenges associated to adopting generative AI tools, perceived usefulness, and ethical considerations may shape their attitudes toward AI integration. Additionally, institutional policies and support structures play a crucial role in determining how effectively these technologies can be incorporated into science learning among pre-service science teachers at the University of Education, Winneba especially integrated science teachers.

Given these challenges, it is essential to examine the factors influencing pre-service integrated science teachers' acceptance and use of Generative AI tools in their learning at the University of Education, Winneba. Understanding these influences will help determine how AI can be effectively used to enhance students' conceptual understanding and academic performance in the learning of integrated science at the University of Education, Winneba.

1.3 Purpose of the Study

The purpose of the study was to examine the factors influencing pre-service integrated science teachers' acceptance and use of generative AI tools for learning at the University of Education, Winneba.

1.4 Objectives of the Study

The specific objectives of the study were to:

1. describe pre-service integrated science teachers' utilisation of generative AI tools in learning.
2. examine the behavioural intention of pre-service integrated science teachers to adopt generative AI for learning,
3. examine the ethical concerns and mitigation strategies adopted by pre-service integrated science teachers to deal with the use of Generative AI tools,

4. determine the challenges influencing pre-service integrated science teachers' willingness to integrate generative AI tools into their learning process.

1.5 Research Questions

The following research questions guided the study:

1. To what extent do pre-service integrated science teachers utilise generative AI tools in their learning?
2. what factors influence the behavioural intention of pre-service integrated science teachers to adopt generative AI tools for learning?
3. what ethical concerns do pre-service integrated science teachers have regarding the use of generative AI tools, and how do they mitigate these concerns?
4. what challenges influence pre-service integrated science teachers' willingness to integrate Generative AI tools into their learning process?

1.6 Significance of the Study

The study is significant as it provides insights into the factors influencing pre-service integrated science teachers' acceptance and use of Generative AI tools in their learning. Understanding these factors is essential for promoting AI integration in science education and addressing barriers such as limited awareness, digital literacy challenges, ethical concerns, and institutional support. The findings of this study will inform policymakers, educators, and curriculum developers at the Faculty of Science Education, University of Education, Winneba, by offering evidence-based recommendations for ethical AI adoption. This includes the development of AI literacy programmes, institutional policies, and academic guidelines that ensure pre-service teachers are well-equipped to use AI tools responsibly and effectively in their academic and professional growth. Additionally, the study contributes to improving educational practices by empowering pre-service integrated science teachers with knowledge of how generative AI can enhance learning experiences. By identifying challenges and motivational factors influencing AI adoption, the study supports faculty members and educators in designing AI-supported instructional strategies, assessments, and interactive learning resources that align with students' needs.

Beyond its practical implications, the study adds to the theoretical discourse on AI in education by expanding existing frameworks on technology adoption and digital learning. It provides empirical evidence on the cognitive, pedagogical, and ethical considerations of integrating AI into science education, offering valuable insights for future research on AI-driven learning models and personalised instruction. Overall, the study enhances understanding of how generative AI can be effectively incorporated into pre-service science teacher education. By shaping policies, informing instructional practices, and contributing to academic discussions, it ensures that AI integration in teacher training is ethical, effective, and sustainable, ultimately improving the quality of science education in Ghana and beyond.

1.7 Delimitations of the Study

Delimitations refer to the constraints or boundaries that researchers set to limit the scope of their study (Theofanidis & Fountouki, 2018). These delimitations are essential to ensure that the research remains focused, manageable, and feasible within the available resources, such as time, budget, and expertise. The study focused on only students from the University of Education, specifically those enrolled in integrated science programme. The study also focused only on Level 100 to Level 400 pre-service integrated science students from the Faculty of Science Education. Also, the study was conducted within an academic year (2024-2025). Theoretically the study utilised the second generation of the Unified Theory of Acceptance and Use of Technology

(UTAUT 2), Again, the effect of age, gender and experience as moderators were not examined in the study.

1.8 Limitations of the Study

The flaws, circumstances, or outside forces that restrict your methods and conclusion and are outside your control as a researcher are known as limitations (Ha et al., 2023). This study was subject to certain limitations that must be acknowledged. The research was conducted only among pre-service integrated science teachers at the University of Education, Winneba, which restricts the extent to which the findings can be generalised to pre-service teachers in other institutions across Ghana. The use of self-completed questionnaire data introduces inherent limitations which may influence the precision and honesty of participants' responses regarding their perception and intended use of generative AI tools. The sampling approach, which focused on accessible groups of pre-service integrated science teachers, also introduced the possibility of sampling bias, and may not fully represent the perspectives of all categories of students, particularly those with limited exposure to generative AI tools. Finally, the findings may not be directly applicable to other subject areas where generative AI tools might be employed differently.

1.9 Organisation of the Study

This study is organised into five chapters. Chapter one is the introduction, which comprises the background to the study, statement of the problem, purpose of the study, objectives of the study, research questions, significance of the study, delimitations of the study, and limitations. The second chapter is the literature review which entails an empirical review of existing works in connection to the identified problem under study. Chapter three is the methodology which highlights issues relating to the research design, population, sample population, sampling procedures, research instruments; data collection procedures, data analysis procedures, and the intervention processes employed in the study. Chapter four is the data analysis and findings which involves detailed analysis of data obtained, and specific findings made from them on the observed phenomena. Summary, conclusion, and recommendations are the final chapter of this study, which provides a concise general overview of the content of the project to reflect its outcome, and points out specific recommendations for change and or encourage other researchers to undertake further studies into the problem discussed herein.

1.10 Definition of Key Terms

1. **Generative AI**: Artificial intelligence that generates new content, such as text, images, or educational materials.

2. **Integrated Science**: An interdisciplinary approach to science education that combines multiple scientific disciplines, such as physics, chemistry, and biology.

3. **Pre-service Teachers**: Individuals undergoing training to become professional educators.

4. **Personalised Learning**: Tailored educational experiences that cater to individual students' needs, learning styles, and abilities.

5. Utilisation: Deals with the proficiency, frequency of use, preferred devices, familiarity, and prior experience of using integrated science.

6. **Adaptive Learning**: Educational technology that adjusts its content and difficulty level in response to a student's performance and learning patterns.

7. **Ethical Considerations**: Concerns related to data privacy, algorithmic bias, and transparency in using AI in education.

8. **Teacher Education Programs**: Training programs for pre-service teachers to develop their teaching skills and subject knowledge.

9. **AI-driven Platforms**: Educational platforms that utilize AI technology to provide interactive and adaptive learning experience

CHAPTER TWO

LITERATURE REVIEW

2.0 Overview

The Theoretical framework as well as literature relevant to this study was considered in this chapter. The literature reviewed includes; the Unified Theory of Acceptance and Use of Technology (UTAUT 2), teaching and learning of integrated science, students' knowledge of generative AI, current use of generative AI by pre-service teachers, challenges of integrating generative AI into science learning, effectiveness of generative AI on students' performance, generative AI in science education, impact of generative AI on pre-service teachers, teacher perspectives on AI- facilitated science learning.

2.1 Theoretical Framework

The study was underpinned by the modified Unified Theory of Acceptance and Use of Technology (UTAUT 2) proposed by Viswanath Venkatesh, Michael D. Thong and Xin Xu in 2012. The UTAUT 2 model is an extension of the original UTAUT model, incorporating additional factors that influence technology acceptance, particularly in consumer contexts (Venkatesh et al., 2012). The theory states that behavioral intention and actual technology use are influenced by factors (performance expectancy, effort expectancy, social influence, facilitating conditions) plus the addition of 3 new construct, with age, gender, and experience acting as potential moderators (Venkatesh et al., 2012). The UTAUT aims to explain user intentions to use an information system and subsequent usage behaviour (Al Shamsi et al., 2022a).

The model identifies seven constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2012). Performance expectancy is the degree to which using a technology is perceived to enhance job performance. In the context of integrated science education, students need to perceive generative AI tools as valuable for improving their academic outcomes. Studies by Almahri et al. (2020b) suggest that when students believe these tools can facilitate a better understanding and mastery of scientific concepts, their acceptance increases. Effort expectancy encompasses the ease of use associated with adopting new technology. When students find these tools user-friendly, they demonstrate higher levels of acceptance (Al Shamsi et al., 2022b).

Social influence plays a significant role in shaping students' attitudes toward the adoption of technology. Studies by Canziani and MacSween (2021) demonstrate that peer recommendations and faculty endorsements have a significant impact on the acceptance of generative AI tools among pre-service integrated science students. According to Balakrishnan and Dwivedi (2021), a supportive environment encourages students to engage with these technologies, reinforcing their usage. Facilitating conditions refer to the resources and support systems available to users. Infrastructure, training, and institutional support have a significant impact on students' willingness to adopt generative AI tools (Hassan et al., 2021). Adequate resources must be in place to ensure that students can seamlessly integrate these tools into their learning experiences (Al Shamsi et al., 2022b).

Hedonic motivation relates to the enjoyment and pleasure derived from using technology. Generative AI tools can offer engaging and interactive learning experiences, resulting in increased acceptance among science students (Gansser & Reich, 2021). When students find the use of these tools enjoyable, they are more inclined to adopt them for learning. Price value concerns the perceived costs versus benefits of technology use. According to Gunasinghe et al. (2020), when students evaluate the advantages of generative AI tools against potential drawbacks, their assessment can inform their acceptance of these tools. If students perceive that the benefits outweigh the costs, they are likely to adopt these technologies.

Some scholars have raised concerns about the theory including focus on intention versus behaviour (Ahmed, 2015), generalizability concerns (Tamilmani et al., 2017), parsimony and complexity (Dwivedi et al., 2019), omission or under-examination of variables (Tamilmani et al., 2021), applicability beyond voluntary contexts (Acosta-Enriquez et al., 2024), and methodological and measurement issues (Zhang et al., 2025). Despite these critiques, UTAUT and its extensions have experienced widespread application across multiple domains. Scholars have successfully employed the model in education (Arenas-Gaitán et al., 2011; Šumak et al., 2011), healthcare (Hoque & Sorwar, 2017), mobile and digital services (Venkatesh et al., 2012; Oliveira et al., 2016), and, more recently, in studies exploring artificial intelligence adoption (Dwivedi et al., 2023; Al-Emran et al., 2023). Its continued use highlights both the adaptability and lasting relevance of the UTAUT model in explaining technology acceptance, even as researchers recognise its limitations and work to refine it.

This present study utilised the UTAUT 2 model to examine the factors influencing pre-service integrated science teachers' acceptance and use of generative AI tools in learning at the University of Education, Winneba.

2.1.2 Conceptual Framework

This study adopts the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) developed by Venkatesh et al. (2012) as the guiding framework for investigating the acceptance of generative artificial intelligence (AI) tools in science education. The UTAUT2 model extends the original UTAUT by incorporating additional determinants of technology acceptance to better explain consumer and educational technology adoption. The model originally consists of seven constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit (Venkatesh et al., 2012).

In applying the UTAUT2 model to this study, an initial assessment of the measurement properties revealed that the indicators for Hedonic Motivation fell below acceptable reliability thresholds. This suggests that enjoyment or intrinsic pleasure derived from using generative AI tools did not meaningfully influence adoption within the context of integrated science education. As a result, Hedonic Motivation was removed from the final conceptual model. This empirical modification aligns with the principle that theoretical frameworks may be refined based on contextual evidence, thereby offering a contribution by demonstrating that enjoyment is not a primary determinant of generative AI acceptance in science teaching and learning environments (Duah et al., 2024).

To strengthen the model's applicability to emerging technologies, the study extends the UTAUT2 framework by introducing an additional construct: Ethical Concerns and Mitigation Measures. Generative AI technologies raise important issues related to misinformation, data privacy, bias, intellectual property, and responsible use, factors that strongly influence user trust and acceptance (Al-Kfairy et al., 2024). In educational contexts, these concerns become even more pronounced as teachers and students rely on AI-generated content to support inquiry, experimentation, and cross-disciplinary scientific understanding (Pellas, 2025). The incorporation of ethical concerns as part of the conceptual model captures users' perceived risks associated with generative AI, while the addition of mitigation measures reflects users' confidence in safeguards such as verification practices, transparency mechanisms, accuracy checks, and guidelines for safe AI use.

By integrating ethical concerns and mitigation measures into the UTAUT2 model, the study contributes theoretically by extending technology acceptance research into the domain of generative AI ethics. An area that is increasingly critical yet insufficiently represented in existing models (Mogaji et al., 2024). This addition acknowledges that acceptance of AI tools is not driven solely by usefulness or ease of use, but also by users' assessments of the technology's integrity, safety, and alignment with responsible educational practice.

Based on these considerations, the modified conceptual framework for this study consists of the following core determinants: performance expectancy, effort expectancy, social influence, facilitating conditions, price value, habit and ethical concerns and mitigation measures (added construct). No moderating variables (gender, age, experience) were included in the study, reflecting the refined focus on direct determinants of behavioural intention and use of generative AI tools in science education. This modified framework therefore represents both an empirical refinement of the original UTAUT2 through the removal of hedonic motivation and a theoretical extension through the inclusion of ethical concerns and mitigation measures. These adjustments enhance the robustness and contextual relevance of the model for explaining technology acceptance in the evolving landscape of generative AI-supported science education.

2.1.2.1 Performance Expectancy (PE)

Venkatesh et al. (2003) defines Performance Expectancy (PE) as 'the degree to which the use of technology will provide benefits to consumers in carrying out certain activities. Therefore, it denotes the degree to which an individual perceives that a virtual assistant can facilitate greater performance and productivity. According to Almahri et al. (2020b), pre-service integrated science students perceive performance expectancy in terms of how generative AI tools enhance their learning outcomes by aiding the comprehension of complex scientific concepts.

According to Al Shamsi et al. (2022a), students who engage with intelligent tutoring systems experience improved comprehension and retention of complex concepts. Also, students utilising AI-driven platforms reported higher grades and better overall performance in science-related courses. User-friendliness of generative AI tools plays a significant role in their acceptance (Almaiah et al., 2019). If pre-service integrated science teachers find these tools challenging or cumbersome, they may be reluctant to adopt them. Research indicates that students who use AI-enhanced resources report improved academic performance and understanding (Ye et al., 2020). Previous studies have supported the effect of this variable on the use of AI in science learning and its influence on students' adoption of AI (Kessler & Martin, 2017).

2.1.2.2 Effort Expectancy (EE)

Venkatesh et al. (2003) defines effort expectancy as the degree of ease associated with using the system. In the context of the study, it refers to the perceived ease of use of generative AI and how AI tools can enhance learning processes and outcomes by supporting the comprehension of complex scientific theories and the appreciation of practical outcomes (Almahri et al., 2020a). This factor is considered a fundamental predictor of technology adoption in educational and research settings (Wirtz et al., 2019). The user-friendliness of generative AI tools is crucial for facilitating a deeper understanding of scientific principles and promoting their practical adoption among students. If AI tools are complicated and require significant effort to learn, students may resist using them (Almaiah et al., 2019).

According to Chopra (2019), intuitive user interfaces and clear instructional guidance increase the likelihood that students will embrace new technologies. The objective, therefore, is to have users achieve a positive perception of the degree of ease (Venkatesh et al., 2012). Fridin and Belokopytov (2014) showed that confidence in one's ability to handle technical systems significantly influences the intention to use them.

2.1.2.3 Social Influencer (SI)

Social influence is the extent to which consumers perceive their significant others (like family and friends) believe they should use a particular technology" (Ibrahim et al., 2017). In the context of the study, it refers to the degree to which students believe in the importance of teachers, colleagues, students, friends, and even family in supporting their use of AI tools in learning and appreciating scientific principles and theories, as well as tasks (Gunasinghe et al., 2020). The SI-based variable models an individual's beliefs and behaviour through the interactional mechanisms of compliance, internalization, and identification (Moriuchi et al., 2021).

A Previous study by Moriuchi et al. (2021) provided empirical evidence of the impact of SI on the use of technology in various contexts. The role of teachers, peers, mentors, and family influences students' attitudes towards AI tools (Lu et al., 2021). Study by Twum et al. (2021) suggests that when students actively engage with AI tools, others are more likely to follow suit, underscoring the significance of social dynamics in technology adoption.

2.1.2.4 Facilitating Conditions

Facilitating conditions are consumers' perceptions of the resources and support available to perform a behaviour" (Venkatesh et al., 2012). Underlying this perception is the idea of acceptance; an information system depends on a preliminary assessment of one's ability to master the new technology (Wong et al., 2024). Students need to perceive the presence of a solid support infrastructure that facilitates the learning and use of technology, as the usefulness of a technological device depends on the active presence of reducing conditions in a given environment (Canziani and MacSween, 2021). This scenario is particularly relevant in the context of AI-based technology, especially for the teaching of science, whether for individual or organisational use; it is necessary to have infrastructure that facilitates its use (Grover et al., 2022). Study by Gansser and Reich (2021) demonstrate that effective implementation necessitates adequate technological infrastructure, comprehensive training programs, and institutional support that foster educators' and students' confidence in utilising advanced tools, such as generative AI.

2.1.2.5 Price Value

Venkatesh et al. (2012) define price value as the cognitive trade-off that consumers make between the perceived benefits of apps and the cost of using them. Therefore, price value is a measure of the net benefit that students obtain by using AI technology in the field of science. Students' perceptions regarding the affordability and accessibility of generative AI tools can influence their decision to adopt these technologies (Ye et al., 2020). The affordability and accessibility of generative AI tools can play a crucial role in acceptance among students. If the perceived benefits outweigh the costs, adoption is likely to increase (Balakrishnan & Dwivedi, 2021). People are always out to maximise net profit, which implies that if the adoption and use of technology generate positive gains, individuals will accept the associated costs (Fe-Yen Chen et al., 2023)

Previous studies have confirmed the effect that price value has on technology adoption, such as AI use, a process that is inherently enhancing and, as such, provides a positive feeling and impact on users (Moorthy et al., 2019). Students' perceptions regarding the cost and accessibility of generative AI tools can influence their decision to adopt these technologies. Also, the studies found that when students evaluated the benefits of AI tools against their costs, positive perceptions led to heightened acceptance rates (Twum et al., 2021). Studies conducted by Hassan et al. (2021) confirm that price value and behavioural intention are closely related, positively improving intentional behaviour and adoption due to the novel perception that it increases satisfaction.

2.1.2.6 Habit

The habit is the extent to which individuals tend to perform behaviour automatically due to learning" (Venkatesh et al., 2012). As a consequence of repeated performance, when people internalise habits, they may not consciously think about, realize, or evaluate the reasons behind their actions. In the context of AI used based on students' scientific learning, habit enables the formation of a symbiotic relationship between the user (student) and the technology (AI) (Nanda et al., 2024).

Hence, habit is not only an explanation for daily routines (Yen and Wu, 2016) but also an essential factor that determines the degree of user engagement with this type of technology (Perez-Vega et al., 2021). The continuous use of AI technology enhances students' creativity in approaching scientific problems differently, as it not only aids in learning but also serves as an essential tool in research and fosters a better appreciation of scientific principles (Gunasinghe et al., 2020).

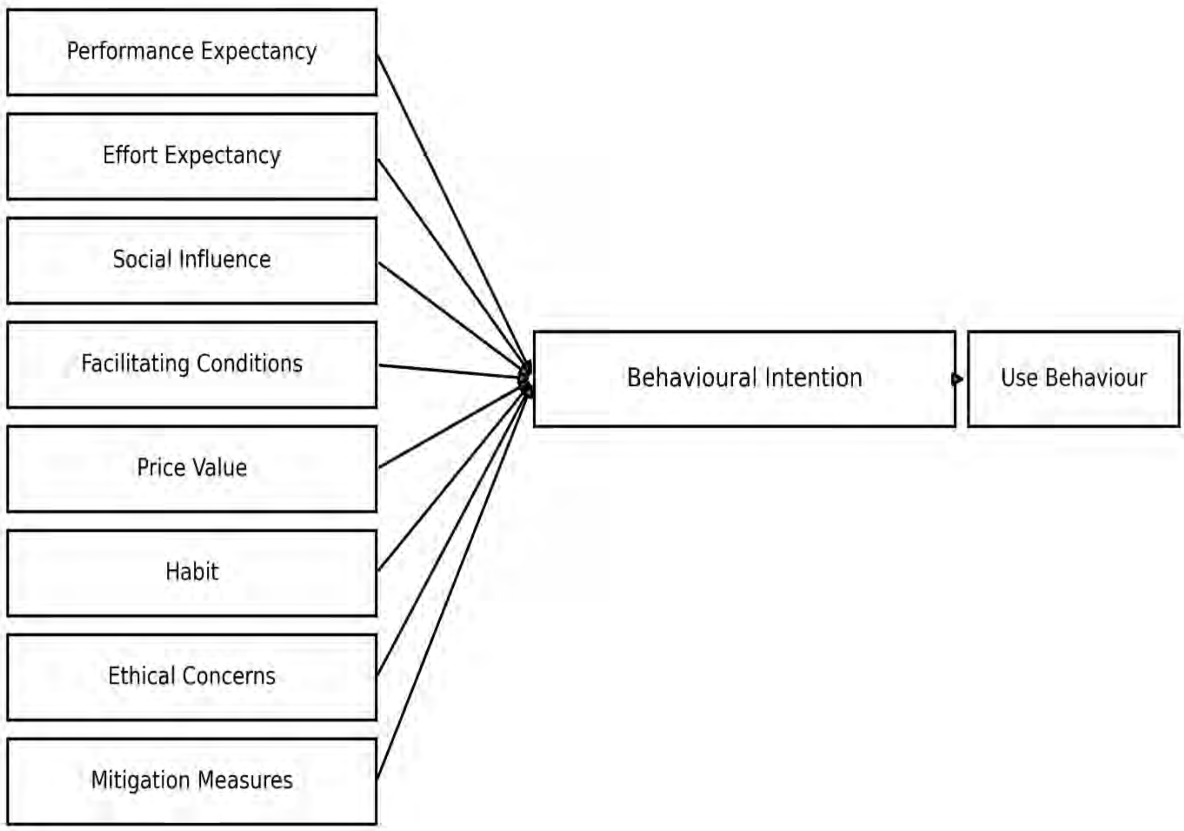

Fig 1. Researcher's Modified Conceptual Framework (Uthman, 2025).

INTERPLAY BETWEEN THE THEORETICAL AND CONCEPTUAL FRAMEWORK

The interplay between the conceptual and theoretical frameworks regarding the modified UTAUT2 model highlights the multidimensional nature of students' acceptance and use of generative AI tools (Yang & Lee, 2019). According to Twum et al. (2021), understanding how constructs such as performance expectancy, effort expectancy, social influence, and others fit within broader educational contexts can help researchers and practitioners design more effective interventions to foster technology adoption.

The conceptual framework provides the necessary conditions and considerations for the theoretical framework. By identifying specific variables and contextual factors that influence technology acceptance, the conceptual framework informs the constructs outlined in the UTAUT2 mod. For example, the inclusion of contextual factors such as prior technology experience helps elucidate why specific constructs, like effort expectancy, may have varying impacts among different student groups (Mishra *et al.,* 2021). Conversely, the theoretical framework grounds the conceptual framework in established theories and empirical findings (Gunasinghe *et al*., 2021).

According to Twum et al. (2021), the UTAUT2 model serves as a foundation for understanding the dynamics of students' acceptance of technology. It offers a structured approach to investigating how individual constructs, such as performance expectancy and social influence, shape students' attitudes and behaviours towards generative AI tools. The interplay between the two frameworks can create a feedback loop. Insights gained from exploring how contextual factors affect UTAUT2 constructs can lead to refinements in the conceptual framework, which in turn may prompt further empirical investigations to test and validate the theoretical constructs (Venkatesh *et al.,* 2016). For instance, if research finds that prior experience significantly enhances performance expectancy, this information can influence the way educators design training programs around generative AI tools (Venkatesh *et al.,* 2012).

2.2 Teaching and Learning of Integrated Science

The teaching and learning of Integrated Science in Ghana have received considerable attention from researchers and policymakers due to its significance in national development. Science education serves as the foundation for technological advancement, and as such, its effective implementation at the pre-tertiary level is essential for equipping students with the requisite knowledge and skills (Klemencic et al., 2023). Studies have explored various aspects of Integrated Science education, including curriculum design, instructional strategies, teacher preparedness, student engagement, and the challenges associated with its implementation in Ghanaian schools. Research has shown that the curriculum for Integrated Science in Ghana is structured to provide students with a broad understanding of scientific concepts across biology, chemistry, and physics (Owusu et al., 2022). This interdisciplinary approach is intended to help students appreciate the interconnectedness of scientific knowledge and apply it to real-life situations. However, several studies indicate that the practical aspect of the curriculum is often not effectively implemented due to a lack of resources and inadequate laboratory facilities (Ampadu & Agyeman, 2021). Many schools, particularly those in rural areas, struggle to provide hands-on experiences, which are necessary for reinforcing theoretical knowledge and developing students' inquiry skills. Teacher preparedness and instructional strategies have also been widely studied in relation to the teaching of Integrated Science in Ghana. Research suggests that many science teachers lack the necessary pedagogical skills to effectively deliver integrated content (Adjei et al., 2023). As some teachers adopt student-centred approaches, such as inquiry-based learning, cooperative learning, and problem-solving techniques, others rely heavily on lecture methods, which limit students' active participation in the learning process (Mensah & Boateng, 2021). The effectiveness of instructional methods has been linked to teachers' professional development and exposure to modern teaching strategies. Training programs and workshops have been recommended to enhance teachers' competencies and encourage the use of innovative instructional methods that promote student engagement (Nkrumah et al., 2020).

The role of assessment in Integrated Science education has also been examined in recent studies. The use of both formative and summative assessments is emphasised in the curriculum to monitor student progress and provide feedback for improvement. A study has found that most teachers focus more on summative assessments, such as standardized tests and examinations, rather than continuous assessment methods like concept mapping, peer assessment, and reflective journals (Asare & Osei, 2021). This overemphasis on high-stakes testing often leads to rote memorization, rather than a deep understanding of scientific concepts. Scholars advocate for a balanced assessment approach that incorporates alternative assessment methods to better evaluate students' conceptual understanding and practical skills (Baidoo & Antwi, 2023). Student engagement in Integrated Science has been a topic of interest among researchers, with studies showing mixed results about students' attitudes toward the subject. Some studies indicate that students find Integrated Science difficult due to abstract concepts and complex calculations, particularly in physics and chemistry components (Dapaah & Ofori, 2022; Tenzin et al., 2022; Ogunkola & Samuel, 2011). Others suggest that when students are exposed to practical and interactive learning experiences, they develop a positive attitude toward the subject and perform better academically (Asiamah et al., 2021). Gender disparities have also been noted in science education, with research highlighting that female student tend to have lower interest and confidence in Integrated Science compared to their male counterparts (Acheampong et al., 2023). Efforts to bridge this gap include targeted interventions, mentorship programs, and gender-sensitive teaching approaches aimed at increasing female participation in science (Adu-Gyamfi et al., 2022). Challenges associated with the teaching and learning of Integrated Science in Ghana have been widely documented. Studies reveal that inadequate teaching and learning materials, including textbooks, laboratory equipment, and ICT resources, hinder effective science education (Asano et al., 2021; Twumasi & Anokye, 2021; Ghavifekr et al., 2016). Teachers often resort to improvised materials, which may not always be effective in conveying scientific concepts accurately. Additionally, large class sizes, particularly in public schools, make it difficult for teachers to provide individualized attention to students, further affecting learning outcomes (Owusu-Ansah & Boadi, 2023). Another major challenge is the limited professional development opportunities for science teachers. While workshops and in-service training programs exist, they are often irregular and not widely accessible to all teachers (Kusi & Addo, 2021).

Several interventions have been proposed to improve the teaching and learning of Integrated Science in Ghana. The incorporation of technology in science education has been suggested as a means to enhance instructional delivery and student engagement (Abakah & Mensah, 2023). The use of virtual laboratories, augmented reality, and digital simulations has been found to improve students' understanding of abstract concepts, particularly in schools where physical laboratory resources are inadequate (Odoom & Yeboah, 2022). Additionally, government policies aimed at providing adequate resources and infrastructure for science education have been emphasised as critical for improving learning outcomes (Adomako & Frimpong, 2023). Recent studies suggest that collaborative efforts among educators, policymakers, and stakeholders are necessary to address the challenges facing Integrated Science education in Ghana. Effective policy implementation, continuous professional development for teachers, and investment in science education infrastructure are key to ensuring that students acquire the scientific knowledge and skills needed for national development (Boateng & Amponsah, 2022). Research continues to highlight the need for a more practical, student-centered, and technologically enhanced approach to teaching Integrated Science to make the subject more engaging and relevant to students' everyday lives (Obeng & Tetteh, 2023).

2.3 Behavioural Intention of Pre-Service Science Teachers in Adopting Generative AI Tools

Generative Artificial Intelligence (AI) has emerged as a transformative force in education, potentially enhancing teaching and learning by providing personalised instruction, automating assessments, and facilitating content generation (Guettala et al., 2024a). The increasing availability and accessibility of AI-based tools, such as ChatGPT, DALL-E, and other generative models, have created opportunities for educators and students to engage with learning materials in novel and innovative ways (Zawacki-Richter et al., 2019). Understanding pre-service integrated science teachers' behavioural intention to adopt these learning tools is crucial for ensuring effective integration into learning (Ramnarain & Ndlovu, 2023). Behavioural intention, which reflects the motivation and willingness of individuals to engage in a particular behaviour, is influenced by various psychological, technological, and contextual factors (Hasbi et al., 2023a). For pre-service integrated science teachers at the University of Education, Winneba (UEW), exploring these influences provides insights into how generative AI tools can be effectively adopted to learn integrated science (Acheampong & Boateng, 2023). Adopting technology in education has been widely examined through established theoretical models, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Ahmad, 2015). Davis (1989) proposed TAM, which suggests that two key factors, perceived usefulness and perceived ease of use, affect an individual's intention to use a particular technology. Perceived usefulness refers to the extent to which a person believes that using a technology will enhance their performance, while perceived ease of use reflects the belief that using the technology will require minimal effort. In the context of generative AI, pre-service integrated science teachers' willingness to adopt

AI tools may depend on how beneficial they perceive these tools to be in enhancing learning effectiveness and simplifying complex scientific concepts. A study conducted by Zhai et al. (2021) found that perceived usefulness and perceived ease of use significantly influenced students' intention to use AI tools in science classrooms. Students who believed that AI could improve their engagement and learning outcomes were more likely to adopt AI-based instructional strategies (Fitria, 2021).

The UTAUT model, developed by Venkatesh et al. (2003), extends TAM by introducing additional factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy reflects the degree to which an individual believes that using a technology will lead to improved performance, while effort expectancy measures the perceived ease of using the technology. Social influence refers to the degree to which individuals perceive those others (such as peers, mentors, or educational institutions) expect them to use the technology. Facilitating conditions involve the availability of resources and support to enable effective use of the technology. In the context of generative AI, these factors play a significant role in shaping the behavioural intention of pre-service science teachers. A study conducted by Kim and Lee (2022) in South Korea revealed that social influence and facilitating conditions had a strong positive impact on the adoption of AI tools among students. Similarly, in Ghana, Kori (2024) found that institutional support and peer influence significantly enhanced pre-service teachers' readiness to adopt digital learning tools.

Ajzen's (1991) Theory of Planned Behaviour (TPB) further provides a psychological framework for understanding behavioural intention. According to TPB, behavioural intention is influenced by three key factors: attitude toward the behaviour, subjective norms, and perceived behavioural control. Attitude reflects the individual's positive or negative evaluation of using the technology, subjective norms capture the social pressure to adopt the technology, and perceived behavioural control measures the individual's perception of the ease or difficulty of performing the behaviour. In the case of generative AI adoption among pre-service integrated science teachers, a positive attitude toward AI technology and supportive peer and institutional environments are likely to increase willingness to adopt these tools. Research by Wang and Huang (2023) in Taiwan indicated that students with positive attitudes toward AI and a high sense of self-efficacy in using technology were more inclined to integrate AI tools into their learning process and gradually into their teaching activities in the future. Perceived usefulness and ease of use are critical determinants of AI adoption among pre-service integrated science teachers. Generative AI tools offer the potential to provide real-time feedback to students and generate customised learning content (Ullmann et al., 2024). For instance, AI-generated simulations and visualisations of scientific phenomena can enhance student understanding of abstract concepts (Lee & Song, 2024). However, the complexity of some AI tools may pose a barrier to adoption, especially for pre-service integrated science teachers with limited technological expertise (Sun et al., 2024). A study by Zhang et al. (2022) in China found that while students appreciated the potential of AI in improving learning outcomes, challenges related to technical complexity and lack of training limited their willingness to adopt these tools.

Social influence and peer support also play a crucial role in shaping the behavioural intention of pre-service integrated science teachers toward generative AI (Sun et al., 2025). When mentors, colleagues, and educational institutions endorse the use of AI tools, pre-service integrated science teachers are more likely to develop positive attitudes toward adopting such tools. A study by Li et al. (2021) found that pre-service science teachers who participated in professional learning communities focused on AI were more confident and willing to use AI-based instructional strategies. At UEW, fostering a culture of technological innovation through peer collaboration and institutional support could enhance pre-service integrated science teachers' willingness to experiment with generative AI tools (Takyi, 2024). Additionally, exposure to successful case studies and best practices in AI adoption can reinforce positive perceptions and reduce resistance to change. Facilitating conditions, such as access to training, infrastructure, and technical support, are essential for the successful adoption of generative AI tools (Prasad, 2024). Pre-service integrated science teachers at UEW may face challenges related to limited internet connectivity, lack of access to AI-compatible devices, and insufficient training opportunities. Research by Tan et al. (2023) in Singapore highlighted that students who received comprehensive training in AI applications were more confident and effective in using these tools in their teaching. Providing targeted training programs and ensuring that AI tools are integrated into teacher education curricula can address these barriers and improve adoption rates. Moreover, addressing concerns related to data privacy, security, and ethical use of AI is critical for building trust and confidence among pre-service teachers (Chen et al., 2023).

Despite the potential benefits, several challenges may hinder the adoption of generative AI tools among pre-service integrated science teachers. Concerns about plagiarism, over-reliance on AI-generated content, and the accuracy of AI-generated information are common barriers (Ogwueleka, 2025). Additionally, the fear of AI replacing traditional teaching roles may create resistance among some teachers. A study by Chen et al. (2024) in Hong Kong revealed that teachers were hesitant to adopt AI tools due to concerns about the reliability and originality of AI-generated content. Providing guidelines on responsible use, encouraging critical evaluation of AI-generated outputs, and emphasising the complementary role of AI in enhancing, rather than replacing, human teaching can address these concerns. The behavioural intention of pre-service integrated science teachers at the University of Education, Winneba, to adopt generative AI tools for learning is influenced by a complex interplay of perceived usefulness, ease of use, social influence, facilitating conditions, and individual attitudes. Established theoretical models such as TAM, UTAUT, and TPB provide a comprehensive framework for understanding these factors. While generative AI offers significant potential to enhance science teaching and learning, addressing barriers related to technical complexity, access to resources, and ethical concerns is essential for successful adoption (Huang et al., 2025). Fostering a supportive institutional environment, providing targeted training, and encouraging peer collaboration are key strategies for promoting the effective use of generative AI tools in science education (Kori et al., 2024).

2.4 Students' Knowledge of Generative AI

The widespread availability of smartphones and internet connectivity has positioned artificial intelligence (AI) as an integral part of students' everyday lives across many countries. AI-powered applications such as language learning platforms, personalised tutoring systems, generative AI tools, and educational games are increasingly being adopted to support learning (Gordon et al., 2021). Students also engage with AI through voice assistants like Siri, Alexa, and Google Assistant, which are embedded in smartphones and other smart devices (Beirl et al., 2019). These assistants can answer questions, set reminders, play music, and perform various tasks, thereby familiarising students with AI technologies (Oranç & Ruggeri, 2021). Despite this exposure, Chiu et al. (2021) found that many students, particularly in higher education, lack a deep understanding of how these technologies function. This knowledge gap remains a barrier to the full adoption and optimal use of generative AI (Gen AI) in learning. While students are often aware of and may have used generative AI tools, they frequently lack awareness of the mechanisms behind their functioning as well as their ethical and practical implications (Chiu et al., 2021). Although students demonstrate some awareness of how platforms like ChatGPT and automated tutoring systems can support learning, they are often unaware of the underlying processes that make these systems effective. This limited understanding prevents them from critically assessing or fully leveraging such technologies in academic contexts (Fisher et al., 2023). Holmes (2020) further argues that without adequate knowledge, students may struggle to distinguish between meaningful academic support and over-dependence on AI, which could lead to issues of academic dishonesty or unhealthy reliance. The rapid pace of AI development has surpassed the integration of relevant content into higher education curricula, meaning that many students graduate without the skills necessary to critically exploit these tools (Ertmer & Ottenbreit-Leftwich, 2022).

Bridging this gap requires intentional educational interventions that equip learners not only to use AI but also to critically evaluate and harness its potential for academic and professional purposes (Williams, 2024). A lack of understanding about generative AI is particularly concerning in science education, where inquiry-based learning is fundamental. Unlike rote knowledge acquisition, inquiry-based learning emphasises active investigation and questioning. Generative AI has significant potential to support such practices, but only if students first understand its underlying functions (Liu & Wang, 2021). Without this knowledge, AI risks being reduced to a tool for retrieving information, thereby limiting its capacity to stimulate critical thinking and deeper investigation (Li et al., 2022). Generative AI can play a transformative role in facilitating inquiry-based and personalised learning by enabling students to explore complex scientific concepts, run simulations, and generate hypotheses. However, students who lack an understanding of how AI generates content may interact passively with outputs, taking them at face value rather than critically interrogating or analysing them. This undermines the goals of inquiry-based learning, which is central to developing scientific reasoning and problem-solving skills (Jones & Smith, 2023). Students who recognise both the strengths and limitations of AI are better positioned to evaluate AI-generated information, test its reliability, and meaningfully apply it to scientific inquiries (Brown & Thompson, 2023).

Educators and facilitators therefore play a critical role in mediating students' interactions with generative AI. They must possess sufficient knowledge of AI technologies to guide students in understanding complex patterns and trends in scientific data (Johnson, 2023). Generative AI can also support pre-service teachers in analysing large datasets quickly, providing opportunities to develop advanced research and analytical skills (Baig et al., 2023). Facilitators can further enhance engagement by integrating practical AI-based activities into lessons. For example, in climate science, AI can be used to forecast environmental conditions from current data, helping students to visualise the effects of human activities on ecosystems (James & Patterson, 2022). Such applications not only make learning more interactive but also increase the relevance of science education to current global challenges. In addition, encouraging students to critically question the ethics and reliability of AI-generated data helps to foster reflective thinking (Smith & Jones, 2022). This approach equips learners with the ability to engage responsibly with AI technologies while preparing them for their growing role in scientific research and professional practice. Ultimately, generative AI offers immense opportunities for advancing inquiry-based science education, but its effective use requires both educators and students to engage with it critically and thoughtfully.

2.5 Current Use of Generative AI by Pre-Service Teachers

The emergence of Generative Artificial Intelligence (Gen AI), such as ChatGPT, is reshaping education and has the potential to significantly influence how pre-service teachers learn and prepare for future classroom practices (Zhai et al., 2023). Generative AI, known for its ability to mimic human-like cognitive functions across diverse tasks, has been highlighted as transformative in teaching, learning, and research (Polat, 2023; Rahman & Watanobe, 2023). For instance, Chen et al. (2020) demonstrated that a conversational agent powered through generative models could provide personalised mathematics tutoring, offering explanations tailored to students' misconceptions and adapting to their levels of understanding. Such findings suggest that pre-service integrated science teachers can benefit from similar systems that enhance personalised support during their training. Beyond tutoring, AI-powered chatbots and virtual assistants are increasingly being integrated into education to provide instant support, respond to student queries, and offer academic guidance (Xuesong et al., 2021). These applications highlight opportunities for pre-service integrated science teachers to engage with technologies that mirror the kinds of support tools they might one day recommend to their own students. Generative AI tools, such as intelligent chatbots and content-creation systems, have also been recognised for their capacity to enhance personalisation and foster learner engagement (Luckin et al., 2023). Holmes et al. (2019) emphasised that AI's ability to analyse individual learner data and adapt instruction to diverse needs makes it especially relevant for pre-service teachers as they develop skills in differentiated instruction and inclusive pedagogy.

Research further indicates that generative AI supports the development of critical thinking and problem-solving skills by enabling learners to interact dynamically with content (Baker et al., 2020). For example, pre-service integrated science teachers can use AI-driven algorithms to adjust the difficulty, pace, and content of their studies, creating more engaging learning journeys. Lee (2023) found that students appreciated AI simulations in which historical figures explained events, highlighting the value of AI in supporting diverse learning styles. Similarly, Choi et al. (2023) observed that AI could benefit introverted or nervous students, who may feel more comfortable interacting with AI than with instructors, thereby broadening accessibility. Generative AI can also assist in language translation, making instructional resources accessible across different linguistic backgrounds (Johnson et al., 2023). This functionality is particularly relevant in multilingual contexts such as Ghana, where pre-service teachers often encounter diverse student populations. Moreover, AI platforms can assist with assignments, laboratory work, and calculations, providing both academic and administrative support (Smith, 2022). In the process, pre-service integrated science teachers strengthen their own digital literacy and learn to evaluate information credibility and ethical considerations related to AI adoption (Brown, 2022). Such competencies are essential for preparing future educators to guide students in a technology-rich learning environment.

The simulation of complex scientific phenomena is another notable contribution of generative AI, especially for pre-service integrated science teachers. Virtual laboratories powered by AI can allow them to conduct experiments and analyse data in safe, resource-efficient environments (Baker et al., 2022). Such simulations not only enhance inquiry-based learning but also build capacity for critical thinking and scientific reasoning. Pane et al. (2015) highlighted the value of individualised feedback in learning, a feature increasingly enabled via AI systems. However, challenges remain, pre-service teachers must be aware of the risks of overreliance, academic dishonesty, and plagiarism (Hattie & Donoghue, 2023). Despite its promise, the integration of AI in education is not yet fully realised. Ertmer and Ottenbreit-Leftwich (2022) noted that teachers' beliefs and attitudes strongly shape technology adoption, with reluctance often rooted in insufficient training or scepticism about AI's reliability. Ertmer (2022) further argued that without adequate professional development and institutional support, teachers may fail to harness AI's benefits for student learning. Harris and Hofer (2023) also highlighted that concerns around technical support, professional development gaps, and ethical implications create barriers to adoption. Professional development is therefore critical to equipping pre-service integrated science teachers with both the technical expertise and the pedagogical strategies required for effective AI integration (Harris & Hofer, 2023). Targeted training programs can help pre-service integrated science teachers explore how AI tools foster collaborative learning, support inquiry, and strengthen critical thinking. By building confidence and competence, pre-service integrated science teachers are more likely to leverage generative AI in their future classrooms to enrich learning experiences. As AI technology continues to evolve, its potential to transform science education grows, offering opportunities to personalise instruction, increase efficiency, and better prepare pre-service integrated science teachers for the demands of 21st-century classrooms.

2.6 Ethical Concerns Associated with The Use of Generative AI in Learning

The integration of Generative Artificial Intelligence (GenAI) into education has introduced significant ethical concerns that must be addressed to ensure responsible use. A central issue is the risk of misinformation and "hallucinations" in AI-generated responses, where false or misleading information is presented as fact. Since large language models are trained on vast datasets that may include inaccurate or biased content, they can inadvertently propagate misinformation in academic settings. Such over-reliance on AI systems, without critical evaluation, can diminish students' ability to engage in analytical thinking and undermine the reliability of learning (Zhai et al., 2024). Plagiarism and academic integrity also represent pressing challenges. The ability of generative AI tools to generate essays, reports, and even research papers create an older area in distinguishing between student-authored work and AI-generated text. Without clear boundaries, the use of such tools may erode academic honesty and devalue educational qualifications. Educators report growing concern over algorithmically-driven writing and emphasise the need for updated academic integrity policies and guidelines to ensure responsible use of AI tools in coursework (Gustilo et al., 2024; Tan, 2024).

Data privacy and security concerns are equally significant. Generative AI systems often require access to sensitive user data, raising questions about how this information is collected, stored, and used. Inadequate safeguards can expose students and educators to risks of profiling, surveillance, and data misuse. As such, institutions must adopt robust data protection protocols while equipping pre-service teachers with the knowledge to critically assess the privacy implications of AI technologies (Yan et al., 2023). Another challenge involves bias and discrimination. Generate AI systems reflect patterns in their training data, which can lead to the reinforcement of stereotypes or the exclusion of marginalised groups. This perpetuation of societal biases poses ethical risks in educational contexts, where inclusivity and equity are paramount. Research highlights the need for deliberate interventions in both dataset design and algorithm development to mitigate such biases and promote fairness in AI-supported learning environments (Williams et al., 2024). Intellectual property (IP) and copyright concerns also arise in the context of AI-generated content. The blurred boundaries of authorship, whether the "creator" is the user, the AI, or the model developers complicate existing legal and educational frameworks. These unresolved issues have implications for pre-service teachers, who must be equipped with the knowledge to navigate questions of attribution and ownership in academic and professional settings (Yan et al., 2023).

Environmental sustainability is another emerging ethical consideration. Training and operating large AI models require vast computational resources, resulting in substantial energy consumption and carbon emissions. As AI becomes more integrated into education, concerns about its ecological footprint highlight the importance of developing energy-efficient models and adopting sustainable practices (Yan et al., 2023). Finally, equitable access to AI technologies is an enduring concern. Students from disadvantaged backgrounds may lack the resources needed to engage meaningfully with advanced AI tools, thereby exacerbating existing educational inequalities. Ensuring equal access to AI-driven learning opportunities is critical for pre-service teachers, who will play a role in fostering inclusive learning environments that bridge rather than widen the digital divide (Williams et al., 2024). In conclusion, while generative AI presents transformative opportunities for education, its adoption must be guided by ethical principles. Addressing challenges related to misinformation, academic integrity, privacy, bias, intellectual property, environmental sustainability, and equitable access is crucial for preparing pre-service integrated science teachers to use AI responsibly. Establishing robust ethical policies, promoting digital literacy, and equipping educators with strategies for critical engagement will ensure that AI enhances rather than undermines educational practice.

2.7 Challenges of Integrating Generative AI into Science Learning

The integration of Artificial Intelligence (AI) in education holds immense promise for revolutionising the learning experience, but it also presents a host of challenges that must be thoughtfully addressed to ensure its effective and ethical use. Various authors recognise challenges associated with this technology related to plagiarism and academic integrity (Crawford et al., 2023; Currie, 2023), bias (Cooper, 2023), inaccuracy and misinformation (Abbas et al., 2024), data and privacy concerns (Wang et al., 2023; Tredinnick & Laybats, 2023), and copyright (Strowel, 2023). In the pursuit of educational advancement through AI, it is imperative to address these challenges with a commitment to ethical and responsible use, ensuring that AI enhances learning experiences and improves educational outcomes for all students. While AI's role in education is undoubtedly transformative, it is essential to approach this integration cautiously. The possibility of using generative AI as a plagiarism tool affecting academic integrity appears to be the main concern. The first question when discussing the threat of plagiarism and its potential impact on academic integrity is to examine the capabilities of Large Language Models (LLMs). While they can generate 500-word essays, the content often lacks depth and proper citations. ChatGPT is known for its human-like writing, with studies showing even expert scientists can struggle to distinguish between its AI-generated abstracts and those by humans (Else, 2023). While ChatGPT can undeniably be used for academic cheating, at the point of writing, there is limited actual evidence of mass-scale cheating taking place. A survey in January 2023 by the Quality Assurance Agency (QAA, 2023), with over a thousand university students, revealed that more than one-third were using ChatGPT for their assessments. Among these, many acknowledged that it was unethical but still continued to use it

(Johnston et al., 2024). Increasing reliance on this tool amplifies concerns about academic honesty and plagiarism risk (Stokel Walker, 2022).

Generative AI also has the potential to provide inaccurate or misleading information. AI outputs may sometimes contain errors or require careful interpretation, leading to student misunderstandings (Holstein et al., 2019). For instance, Kumar (2023) analysed AI-generated responses to academic writing prompts and found that while the texts were mostly relevant, they contained inappropriate references and lacked personal perspectives that AI cannot produce. Misleading outputs can impair students' grasp of ideas, requiring educators to carefully verify created content to ensure accuracy. For example, ChatGPT may generate a faulty solution to a stoichiometry problem in Chemistry, which could mislead students. Furthermore, AI-produced feedback depends heavily on the quality of input data (Roll & Wylie, 2016). For second language learners, crafting effective prompts may be particularly challenging, raising the risk of overreliance and diminishing genuine writing skill development (Warschauer et al., 2023). In addition, the content produced by generative AI may be biased, inaccurate, or harmful if the dataset on which a model was trained contains such elements (Harrer, 2023). AI-generated images, for example, may contain nudity or obscenity and can be misused for malicious purposes such as deepfakes (Maerten & Soydaner, 2023). Since AI-generated output is often undetectable by plagiarism software, it is difficult to determine authorship or originality (Peres et al., 2023). As Chan (2023) notes, this "raises the question of what constitutes unethical behaviour in academic writing, including plagiarism, attribution, copyrights, and authorship in the context of AI-generated content." Similarly, Zhai (2022) cautions that text-to-text generators like ChatGPT may compromise the validity of assessment practices, particularly those involving written assignments. The widespread use of generative AI therefore poses a serious challenge to academic integrity in higher education.

Beyond academic honesty, integration challenges also relate to technological, ethical, and pedagogical factors. Ethical issues such as data privacy and surveillance remain major concerns, as AI systems collect and analyse sensitive student data (Iris, 2024). Moreover, inequities in access to AI tools risk exacerbating educational divides (Cotton et al., 2023). For many institutions, particularly in developing contexts, the financial and infrastructural demands of implementing AI remain prohibitive (Dwivedi et al., 2023). Teachers also face difficulties in adapting to AI-assisted pedagogies; many lack training in both technological and curricular design (Umesh et al., 2024). Some educators even fear that AI might undermine their professional role or introduce bias in assessment (Holmes et al., 2021). Pre-service teachers themselves may feel overwhelmed by the influx of AI technologies if not well integrated into their learning contexts (Abhiram et al., 2024). While AI can enhance personalisation, it cannot substitute for social engagement, emotional support, and teacher guidance, which remain critical for holistic development (Cecilia & Louisa, 2023). Thus, while the benefits of generative AI underscore its potential as a valuable tool for enhancing science learning, its challenges highlight the urgent need for carefully designed integration strategies, ongoing research, and robust ethical safeguards (Cecilia & Wenjie, 2024; Muhammad et al., 2024).

2.8 Effectiveness of Generative AI on Pre-Service Students' Performance

In the rapidly evolving field of education, Artificial Intelligence (AI) has emerged as a transformative tool with the capacity to adapt, analyse, and automate learning processes. Generative AI (GenAI), in particular, has been recognised for its potential to personalise learning, enhance student engagement, and improve academic performance

(Zaman, 2023). Studies suggest that generative AI tools can serve as valuable research aids, helping pre-service integrated science teachers generate ideas, synthesise information, and summarise large volumes of text to support writing and data analysis. Such affordances are believed to contribute to improved academic outcomes at institutions like the University of Education, Winneba (Malik et al., 2023). A central advantage of generative AI lies in its capacity for personalised learning. By analysing learner data, AI systems can monitor progress, diagnose learning gaps, and adjust instructional strategies accordingly (Ellikkal & Rajamohan, 2024). This adaptive capability allows students to learn at their own pace and according to their individual styles, thereby boosting motivation and performance (Luckin et al., 2021). Holmes et al. (2019) further highlight the role of AI in formative assessment, where immediate, personalised feedback helps students identify strengths and weaknesses, ultimately increasing the effectiveness of the learning process. Similarly, Hariguna et al. (2023) argue that AI's ability to provide real-time feedback enhances students' comprehension before advancing to new material.

Case studies demonstrate that generative AI tools can improve learning outcomes when implemented effectively. For example, the adaptive learning platform Squirrel AI in China has shown marked improvements in student achievement (Zawacki-Richter et al., 2023). Such successes underscore generative AI's potential to create flexible, efficient learning environments. At the same time, researchers caution that AI adoption should be guided by clear pedagogical goals and ethical considerations (Sarkar & Sarkar, 2024). While scholars emphasise the dual narrative of promise and caution (Alali et al., 2024), they agree that careful integration can enable pre-service teachers to harness AI for dynamic and equitable educational opportunities (Bae et al., 2024). Empirical findings on the effectiveness of generative AI remain mixed. Some studies report improvements in academic achievement (Sun & Zhou, 2024), while others note reduced performance among students overly reliant on AI tools. For instance, Wecks et al. (2024) found that students using ChatGPT scored lower on average compared to their peers, raising concerns that excessive dependence may hinder deep learning and critical thinking. In contrast, other research shows that AI-based tutoring systems enhance engagement and academic achievement when applied appropriately (Kaswan et al., 2024; Batsaikhan & Correia, 2023).

Despite its potential, concerns persist regarding the credibility of AI-generated content and the possibility of reinforcing biases present in training data (Ferrara, 2023; Ou et al., 2024). To mitigate these risks, scholars emphasise the need for developing AI literacy among both students and educators (Muthukrishnan et al., 2024; Cacho, 2024). This includes equipping pre-service teachers with skills to critically assess AI output, ensure ethical use, and complement rather than replace traditional pedagogy (Ajani et al., 2024; Tan & Ling, 2024). Thus, while generative AI can significantly enhance pre-service student performance, its successful integration requires balance, critical oversight, and teacher preparedness.

2.9 Generative Artificial Intelligence in Science Education

Science education, which relies on inquiry-based approaches, critical thinking, and experimentation, has seen various AI applications that enhance both instruction and student engagement (Fitria, 2021). Educators and researchers have examined how generative AI can be utilised to support students in developing scientific reasoning, problem-solving abilities, and conceptual understanding of complex scientific phenomena. Recent studies have explored the role of generative AI in providing personalised learning pathways for students with different levels of prior knowledge and learning needs (Oye et al., 2024; Guettala et al., 2024; Tapalova & Zhiyenbayeva, 2022). AI-powered tutors and chatbots have been developed to generate explanations, answer student queries, and provide interactive simulations that allow learners to visualise abstract scientific concepts (Nguyen et al., 2023). These tools enable students to explore concepts at their own pace, reducing the reliance on traditional classroom instruction and fostering independent learning (Zhu & Wang, 2022). The ability of AI models to generate adaptive feedback has been particularly beneficial in subjects such as physics, chemistry, and biology, where students often struggle with complex problem-solving tasks (Kumar et al., 2023). Another area of research has focused on the use of generative AI in laboratory simulations and virtual experiments. Science education traditionally relies on hands-on experiments to help students develop practical skills and a deeper understanding of theoretical concepts. However, many schools, particularly in resource-limited settings, face challenges in providing access to well-equipped laboratories. Virtual laboratories powered by AI-generated content have emerged as an alternative solution, allowing students to conduct experiments in a simulated environment (Chen et al., 2023). These platforms generate interactive scenarios that replicate real-world experiments, providing students with opportunities to engage in scientific inquiry without the constraints of physical resources (Lee et al., 2022).

Studies have shown that students who use AI-powered virtual labs demonstrate improved conceptual understanding and retention compared to those who rely solely on textbook-based instruction (Reginald et al., 2023; Qawaqneh et al., 2023; Ramirez et al., 2023; Cardona et al., 2023). The application of generative AI in science assessment has also been widely studied. Traditional assessment methods often involve standardised tests, which may not fully capture students' critical thinking abilities and problem-solving skills. AI-generated assessments, including automated grading systems and adaptive testing, have been developed to provide a more comprehensive evaluation of student learning (Johnson & Patel, 2023). These systems analyse student responses, generate personalised feedback, and suggest targeted learning interventions based on individual performance. A study has indicated that AI-powered assessments reduce grading bias and allow for a more dynamic and responsive evaluation process, particularly in large science classrooms where individualised feedback is often challenging to provide (Brown & Kim, 2022). Additionally, the ability of AI models to generate open-ended questions and design complex problem-solving tasks has contributed to a more authentic assessment of scientific inquiry skills (Garcia et al., 2023). The use of generative AI in science education has raised concerns related to academic integrity, teacher roles, and ethical considerations. The ability of AI tools to generate high-quality responses has led to discussions on the implications for student learning and originality. Researchers have warned that excessive reliance on AI-generated content may diminish students' ability to develop independent problem-solving skills and critical thinking abilities (Zhai et al., 2024; Çela et al., 2024; Miller et al., 2023). Studies have also demonstrated the need for science teachers to integrate AI tools in a way that complements rather than replaces human instruction (Davis & Thompson, 2023). Teachers play a fundamental role in guiding students through scientific inquiry, facilitating discussions, and promoting hands-on exploration, which AI alone cannot fully replicate. Furthermore, concerns regarding data privacy and bias in AI-generated content have been raised, as these technologies rely on large datasets that may reflect underlying biases present in the training data (Anderson et al., 2023).

The readiness of teachers to effectively integrate AI into science instruction is a challenge for teachers. Many teachers lack the technical skills and professional development opportunities required to implement AI-driven tools effectively. Studies have emphasised the importance of teacher training programs that equip educators with the knowledge and skills necessary to leverage AI for science teaching (Bekdemir, 2024; Williams et al., 2023). Professional development initiatives should focus on enabling teachers to critically evaluate AI-generated content, design AI-supported learning experiences, and address ethical considerations associated with AI use in education (Nelson & Carter, 2023). Without adequate training, the integration of generative AI in science education may lead to inconsistent implementation and varying levels of effectiveness across different learning environments (Richards & Evans, 2023). Studies have suggested that hybrid models, which combine AI-generated content with human instruction, may offer a balanced approach that maximises the benefits of both AI and teacher-led learning (Singh et al., 2023). AI-driven collaborative learning environments, where students engage in peer discussions while utilising AI-generated insights, have been proposed as a way to enhance student engagement and critical thinking (Parker et al., 2023). Additionally, researchers are investigating the development of culturally responsive AI models that align with diverse educational contexts and ensure equitable access to AI-enhanced learning experiences (Okafor et al., 2023). These efforts aim to connect the potential of generative AI while ensuring that its integration supports meaningful and effective science education in Ghana.

2.10 Impact of Generative Artificial Intelligence on Higher Education

In higher education, generative AI has attracted attention for its potential to support teaching, research, and assessment. AI tools assist students by generating adaptive learning resources, analysing progress, and providing real-time feedback (Kutty et al., 2024; Zhang et al., 2023). These applications foster self-directed learning, particularly in disciplines that require analytical reasoning, such as STEM fields (Chen & Liu, 2022). According to Kutty et al. (2024), generative AI is being investigated for its potential to support both students and teachers in various academic activities in higher education, where critical thinking, research, and independent learning are essential. Scholars have examined how AI-driven tools facilitate personalised learning, automate assessment processes, and enhance academic writing while also raising concerns about ethical considerations and the role of instructors in AI-enhanced classrooms. Studies have, therefore, explored how generative AI assists in creating adaptive learning environments that cater to students with diverse educational needs. AI-powered platforms generate customised content, analyse student progress, and recommend resources tailored to individual learning paths (Zhang et al., 2023). Such applications enable students to grasp complex concepts at their own pace, supporting self-directed learning in disciplines that require analytical reasoning, such as science, technology, engineering, and mathematics (Chen & Liu, 2022). The ability of generative AI to provide instant feedback on assignments and suggest improvements has been noted to enhance student engagement and comprehension, particularly in large classrooms where one-on-one interactions with instructors may be limited (Kumar et al., 2023). An area of interest concerns the role of AI-generated content in academic writing and research. AI tools capable of producing well-structured essays, literature reviews, and reports have gained popularity among students and researchers. These tools analyse extensive datasets, generate coherent arguments, and offer citations that support academic work (Brown & Patel, 2023). While some researchers have praised the ability of AI to streamline the research process, others have raised concerns about originality, authorship, and the potential for academic misconduct (Garcia et al., 2023). The accessibility of AI-generated content has led to discussions on how universities should implement guidelines that ensure responsible use while preserving academic integrity (Lee et al., 2023).

The use of generative AI in assessment and grading has also drawn attention. Traditional assessment methods, which often rely on standardised testing and manual grading, are being supplemented with AI-driven evaluation techniques that analyse student responses and provide instant feedback (Nelson & Carter, 2023). AI systems are capable of identifying patterns in student performance, allowing educators to modify instructional strategies accordingly (Anderson et al., 2023). Research has suggested that AI-enhanced assessments help reduce grading bias and ensure consistency in evaluation (Williams et al., 2023). However, concerns have been raised regarding the reliability of AI-generated assessments, particularly in evaluating subjective or creative responses where human judgment remains necessary (Richards & Evans, 2023). AI has demonstrated its potential to enhance higher education, but its widespread adoption raises ethical and pedagogical questions. The ability of AI to generate high-quality academic content has led to debates about its impact on student learning and the development of critical thinking skills (Miller et al., 2023). Over-reliance on AI-generated materials may discourage students from engaging deeply with their coursework, leading to a superficial understanding of concepts (Davis & Thompson, 2023). Additionally, concerns about data privacy and AI bias have been highlighted, as AI models are trained on large datasets that may contain embedded biases (Okafor et al., 2023). Scholars have emphasised the importance of integrating AI into education in a way that supports rather than replaces human instruction, ensuring that students remain active participants in their learning processes (Parker et al., 2023). There is a challenge that involves the readiness of educators and institutions to incorporate AI into the higher education curriculum effectively. Many instructors lack the technical expertise required to evaluate and utilise AI-generated content critically. Studies have underscored the need for professional development programs that equip educators with the skills necessary to integrate AI-driven tools while maintaining pedagogical effectiveness (Singh et al., 2023). Institutions must also establish guidelines that address ethical concerns, ensuring that AI is used responsibly and in ways that enhance, rather than undermine, educational quality (Thelma et al., 2024).

Future studies continue to examine innovative ways of incorporating generative AI into higher education while mitigating its challenges. Studies have proposed hybrid models that combine AI-generated content with instructor-led discussions, fostering a balanced approach that supports both efficiency and deep learning (Nguyen et al., 2023). AI-enhanced collaborative learning environments, where students engage in discussions while leveraging AI-generated insights, have been suggested as a means of fostering engagement and critical thinking (Parker et al., 2023). Additionally, researchers are working on developing AI models that are culturally responsive and aligned with diverse educational contexts, ensuring equitable access to AI-enhanced learning experiences (Chen et al., 2023). These efforts aim to harness the benefits of AI while maintaining the core values of higher education. Further studies have highlighted the impact of generative AI on student collaboration and engagement in higher institutions. AI-driven platforms facilitate peer discussions by summarising key points, generating prompts, and suggesting relevant literature, which enhances students' ability to engage critically with academic material (Tajik, 2025; Rodriguez et al., 2023). In disciplines requiring problem-solving, AI-generated simulations have been utilised to create interactive learning experiences that help students apply theoretical concepts in practical settings (Singh & Patel, 2023). This has proven particularly useful in fields such as engineering, medicine, and environmental sciences, where experiential learning is essential. Concerns regarding the quality and credibility of AI-generated content continue to be a major topic of discussion. Some researchers argue that while AI can streamline content production, it may also perpetuate inaccuracies or reinforce existing biases present in its training data (Henderson et al., 2023). Consequently, scholars emphasise the importance of developing AI literacy among students and educators to ensure responsible use. Universities are beginning to incorporate AI ethics and critical evaluation of AI-generated content into their curricula to equip students with the skills necessary to assess the reliability of AI-assisted research (Turner & Mitchell, 2023). This aligns with broader efforts to integrate digital literacy into higher education, preparing students for a technology-driven academic and professional landscape. The evolving role of teachers in AI-enhanced learning environments is another significant area of research. AI tools have been found to automate administrative tasks, allowing instructors to allocate more time to student mentorship and curriculum development (Wilson et al., 2023). However, studies caution that AI should not replace traditional teaching methods but rather complement them by augmenting personalised learning experiences (Foster et al., 2023). The need for professional development programs focusing on AI integration in education is gaining attention, as educators must adapt to emerging technologies while maintaining pedagogical effectiveness (Grant et al., 2023).

2.11Teacher Perspective on Artificial Intelligence-Facilitated Science Learning

Educators often have varying perceptions regarding the effectiveness, challenges, and ethical considerations of AI in science education. While some view AI as a tool that enhances student engagement and provides personalised learning experiences, others express concerns regarding its implications for teacher roles, classroom dynamics, and student autonomy (Ma'amor et al., 2024). Studies have explored how AI-driven platforms support differentiated instruction, allowing teachers to tailor lessons to students' individual needs. AI-powered tools analyse student responses in real time, providing insights into learning gaps and enabling instructors to adjust their teaching strategies accordingly (Garcia & Lee, 2023). This capability has been particularly beneficial in science education, where complex concepts require adaptive teaching approaches (Patel et al., 2023). Teachers have reported that AI-facilitated learning environments enhance their ability to monitor student progress and provide targeted feedback, which helps students grasp difficult scientific concepts more effectively (Johnson et al., 2022). However, some educators remain skeptical about the extent to which AI can truly personalise instruction without diminishing the human aspects of teaching (Benjamin et al., 2024). The use of AI in science education has also raised discussions about teacher autonomy and the evolving role of educators in technology-enhanced classrooms. AI-driven instructional tools offer efficiency in content delivery and assessment, but some teachers express concerns about over-reliance on automated systems (Choiriyah et al., 2025). There is a perception that AI might lead to a reduction in teacher control over curriculum design, as pre-programmed algorithms dictate instructional pacing and content selection (Harris & Kim, 2023). Teachers have emphasised the importance of maintaining a balance between AI-supported learning and direct teacher intervention to ensure that students receive holistic and meaningful educational experiences (Williams et al., 2023). The ability of AI to generate explanations and solve complex problems has also led to concerns regarding student dependence on technology, with some educators advocating for AI tools to be used primarily as supplementary aids rather than replacements for traditional teaching methods (Nguyen et al., 2022).

One of the most widely discussed aspects of AI-facilitated science learning is its impact on student engagement and motivation. Teachers have observed that interactive AI-driven simulations and virtual laboratories increase student participation, particularly in subjects such as physics and chemistry, where experimental learning is essential (Lopez & Carter, 2023). AI-based platforms allow students to conduct virtual experiments, manipulate variables, and visualize abstract scientific concepts, which has been shown to enhance conceptual understanding (Baker et al., 2023). While many teachers appreciate the dynamic learning experiences that AI can provide, some express concerns about passive learning, where students rely too heavily on AI-generated solutions instead of actively engaging in the problem-solving process (Mitchell & Howard, 2023). To address this, educators emphasise the need for AI tools to be integrated into inquiry-based learning frameworks, where students actively construct knowledge rather than passively receiving information (Zhang & Patel, 2023). Assessment and grading have also been significantly influenced by AI-facilitated learning in science education. Automated assessment systems provide teachers with real-time data on student performance, reducing the burden of manual grading and allowing for immediate feedback (Smith & Wang, 2023). Teachers have found AI-assisted assessments particularly useful for large classes, where personalised feedback would otherwise be time-consuming (Davis et al., 2023). However, concerns have been raised regarding the fairness and accuracy of AI-generated grading, especially in open-ended responses and complex problem-solving tasks (Parker & Nelson, 2023). Some educators argue that while AI can efficiently assess factual knowledge and computational accuracy, human judgment remains essential for evaluating critical thinking, creativity, and scientific reasoning (Chen & Adams, 2023). The potential for algorithmic bias in AI-driven assessments has also been a topic of concern, with teachers advocating for careful calibration and continuous improvement of these systems to ensure fairness across diverse student populations (Henderson & Brown, 2023).

Professional development and teacher preparedness for AI integration have been recurring themes in recent discussions. Many educators feel that they lack adequate training on how to effectively implement AI-driven tools in science instruction (Roberts & Singh, 2023). While AI-based platforms are designed to simplify certain aspects of teaching, the need for teachers to understand how these systems work and how to interpret AI-generated insights remains essential (Miller & Thompson, 2023). Studies have indicated that teachers who receive comprehensive professional development on AI integration demonstrate higher confidence in using technology to enhance student learning (Anderson et al., 2023). Institutions have been encouraged to provide structured training programmed that equip educators with the skills necessary to critically evaluate AI tools and incorporate them effectively into their pedagogical practices (Jackson & Lee, 2023). Without sufficient training, there is a risk that teachers may either underutilize AI-driven resources or become overly reliant on automated systems without fully understanding their limitations (Stevens & Carter, 2023). Teachers have suggested that AI should be designed as a collaborative tool that enhances teacher-student interactions rather than replacing traditional teaching methods (Williams & Foster, 2023). Hybrid models, where AI-generated insights are used to inform teacher-led discussions and classroom activities, have been proposed as a way to maximize the benefits of both AI and human instruction (Harris et al., 2023). The ethical implications of AI in education, including issues of student data privacy and algorithmic transparency, remain areas of ongoing concern for teachers and researchers alike (Zhou & Patel, 2023). As AI continues to evolve, the perspectives of educators will remain central in determining how these technologies are implemented to support meaningful and effective science learning.

2.12 Chapter Summary

Chapter Two presents the theoretical framework and a review of related literature relevant to the study. The Unified Theory of Acceptance and Use of Technology (UTAUT 2) was adopted as the guiding framework, followed by discussions on key themes such as the teaching and learning of Integrated Science, students' knowledge of generative AI, and the current use of generative AI by pre-service teachers. The review also highlights challenges in integrating generative AI into science learning, its effectiveness on students' performance, and its broader role in science education. Furthermore, it examines the impact of generative AI on pre-service teachers and teacher perspectives on AI-facilitated science learning, thereby providing a comprehensive foundation for the study.

CHAPTER THREE

METHODOLOGY

3.0 Overview

This chapter provides an overview of the methodology; it is devoted to the procedures adopted to carry the research on the factors influencing pre-service integrated science teachers' acceptance and use of generative AI tools in learning at the University of Education, Winneba. The chapter entails research philosophy, research design for the study, population, sample, and sampling procedures. The chapter also explains the research instruments used for data collection, validity and reliability of the instrument, data collection procedures, data analysis procedures, and summary.

3.1 Research Philosophy

The positivist paradigm is the research philosophy underpinning this study (Singh, 2019). This philosophy is aligned with the quantitative methodology (Younus & Zaidan, 2022). The study adopted the positivist research philosophy as the foundational worldview that guided how knowledge on generative AI is perceived among pre-service integrated science teachers' and how it influences their behaviour and acceptance of the innovative technology for learning at the University of Education, Winneba (Nyaaba et al., 2024a). The positivist philosophy was most suitable for this study, given its emphasis on objectivity, measurement, and observable reality (Park et al., 2020). Positivism was utilised for this study based on the ontological belief that reality is external, objective, and independent of the perception of the pre-service integrated science teachers at the UEW (Essel, 2016). From an epistemological standpoint, this study holds that valid knowledge on the use of generative AI among pre-service integrated science teachers in UEW arises from empirical evidence that could be measured and quantified (Archibald, 2016). The researcher is assumed to maintain an objective, detached, and independent stance throughout the study, with the aim of minimising biases and ensuring neutrality in the collection and analysis of data on acceptance and use of generative AI for learning among pre-service integrates science teachers at UEW (Baidoo-Anu et al., 2024). This philosophical stance was particularly appropriate for this study, which sought to examine relationships between measurable variables such as students' exposure to AI tools, their perceptions of AI's usefulness in learning, and their actual willingness to adopt such tools for learning at the UEW (Eltahir & Babiker, 2024).

By adopting the quantitative methodology underpinned in the positivist philosophy, the research aimed to apply structured instruments to collect numerical data from a large sample of pre-service integrated science teachers at UEW (Sondlo, 2021). The use of a standardised questionnaire items enabled the collection of quantifiable data on acceptance and use of generative AI tools for learning among pre-services integrated science teachers that was statistically analysed to identify trends, correlations, and differences among pre-services integrated science teachers' subgroups (Ishmuradova et al., 2025). This approach reflected the positivist ideological commitment to using empirical methods to test hypotheses and draw generalisable conclusions (Burton-Jones & Lee, 2017).

It is however acknowledged that quantitative approach unpinned in the positivist paradigm has some limitations. Chief among these is its inability to capture the depth of individual experiences, emotions, and contextual nuances that may influence pre-service integrated science teachers' behaviour towards using generative AI tools for learning (Park et al., 2020). The complexity of factors influencing students' acceptance and use of generative AI tools might include subjective beliefs and contextual dynamics that quantitative data alone may not fully uncover (Shahzad et al., 2025). However, given the study's objectives, which centres on identifying statistically significant patterns and relationships, the choice of a positivist philosophy remains justified and appropriate (Chirkov & Anderson, 2018).

3.2 Research Design

The research design adopted for the study was the descriptive survey design (Creswell & Creswell, 2018). The survey design served as the structured blueprint that was used to guide the entire research process, from data collection to analysis, in order to answer specific research questions on the behavioural intention, use, the ethical concerns and mitigations measures, and the challenges faced by pre-service integrated science teachers in integrating generative AI tools in the learning of integrated science at the University of Education, Winneba (Neuman, 2014). The descriptive survey design was considered appropriate because it enabled the researcher to gather quantifiable data from a large population of pre-service integrated science teachers to describe trends, opinions, or characteristics of those teachers (Siedlecki, 2020). Survey design allowed for the collection of standardised information through structured questionnaires, which helped in identifying patterns and relationships between behavioural intention and use of generative AI tools and its associated variables (Ma & Li, 2024). The design was particularly suitable for this educational research to assess the attitudes, behaviours, or opinions of pre-services integrated science teachers in their natural setting at the University of Education, Winneba without manipulating variables and the settings (Sakyi–Hagan & Hanson, 2022). The responses were analysed using descriptive and inferential statistical methods to draw generalizable conclusions about the population of pre-service integrated science teachers at UEW (Appiah, 2025). The choice of a quantitative descriptive survey design ensured that the findings were based on empirical evidence, thus enhancing the validity and reliability of the results (Duckett, 2021).

3.3 Target Population

The target population of this study comprise all pre-service integrated science teachers within the Department of Integrated Science Education in the Faculty of Science Education at the University of Education, Winneba. The total number of pre-service integrated science teachers from Level 100 to 400 at the Department of Integrated Science were 534.

3.4 Sampling Technique

The proportionate simple random sampling techniques was used to select participants for the study. A simple random sampling technique was used to select participants to ensure representativeness and reduce selection bias (Almusaed et al., 2025). Proportionate simple random sampling ensured that every pre-service integrated science teacher in Levels 100 to 400 in the target population had an equal and unbiased chance of being included in the sample, thereby enhancing the generalisability of the findings (Singh & Masuku, 2014). To determine the appropriate sample size to select from the population of 534 pre-service integrated science teachers studying integrated science, the Krejcie and Morgan's (1970) table for determining the sample size from a given population was used. According to the table, the minimum sample size to be selected from the population of 534 is approximately 220. An additional 35% of the sample size of 220 pre-service integrated science teachers was calculated to cater for missing data, non-responses and uncompleted responses during the study. Therefore, a total of 300 students were randomly selected from the four levels to participate in the study. From this number (300), 75 students each were to be selected from levels 100 to 400 using a lottery method. These students were selected because they have had varying degrees of academic exposure to both Integrated Science content and, increasingly, to the use of generative AI tools in their educational experiences. Including all four levels of students provides a more comprehensive understanding of the factors influencing the acceptance and adoption of such tools across different stages of teacher preparation.

3.5 Research Instrument

In this study, the primary research instrument was a structured questionnaire, specifically designed to collect quantitative data from pre-service integrated science teachers regarding their acceptance and use of generative AI tools in learning (Taherdoost, 2021). The questionnaire was divided into four sections aligned with the research objectives and key variables of the study. The first section included 9 items on demographic information, examples, age at last birthday, gender, level, and utilisation (Proficiency, frequency of usage, devices, prior experience and familiarity). The second section included 48 items on students' acceptance and use of generative AI tools, adopting the UTAUT 2 developed by Venkatesh et al. (2012). The UTAUT 2 used in this study had: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habits. A five-point Likert scale ranging from 1 = strongly disagree, 2 = disagree, 3 = moderately agree, 4 = agree, and 5 = strongly agree. The third section of the instrument was used to collect information on the ethical concerns and mitigation strategies adopted by pre-service integrated science teachers to deal with the use of generative AI tools, a total of 20 items was used. A five-point Likert scale ranging from 1 = strongly disagree, 2 = disagree, 3 = moderately agree, 4 = agree, and 5 = strongly agree was also used to measure the variables in this section. The fourth section of the instrument was used to collect information on the challenges pre-service integrated science teachers face in integrating these tools for academic purposes, a total of 15 items were used. The five-point Likert scale was also adopted in this section, 1= not a challenge, 2= slightly a challenge, 3= challenge, 4= much a challenge, and 5= very much a challenge.

3.6.1 Validity

The questionnaire used in this study was developed based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), as well as prior literature on ethical concern, mitigation measures, and challenges associated with the use of generative AI tools in education. Content validity was established through expert review. The items were reviewed by two lecturers with expertise in educational research and technology integration to assess their clarity, relevance, and alignment with the study objectives. Based on their feedback, revisions were made to improve the accuracy and clarity of certain items. This process ensured that the instrument adequately captured all constructs under investigation.

3.6.2 Pre-Testing and Reliability

Before the main data collection, a pre-test of the questionnaire was conducted to assess the clarity, relevance, and comprehensiveness of the instrument. The pre-test involved a sample of 20 pre-service Biology teachers from the Faculty of Science Education at the University of Education, Winneba, who were not part of the study's population. The primary aim of the pre-test was to identify ambiguities or confusing items and to gather feedback that could inform revisions to the instrument. Based on the responses and suggestions received, no modification was made, which showed clarity and ensured that the instrument aligned with the study's objectives.

The data collected during the pre-test were entered into SPSS version 27 to assess the reliability of the instrument. To assess the internal consistency of the instrument, a pre-test was conducted using responses from pre-service Biology teachers. The data collected was analysed using McDonald's Omega, a robust alternative to Cronbach's Alpha that provides more accurate estimates of reliability (Malkewitz et al., 2023). The results demonstrated that all constructs achieved acceptable to excellent reliability scores (Omega > .70), indicating that the instrument was consistent and suitable for the main study (Kalkbrenner, 2023).

The results showed high levels of internal consistency across all sections of the questionnaire:

Table 1 Reliability Statistics of the Pre-Test

Sub-scale	Number of items	Omega coefficient(ωt)
Performance Expectancy	5	0.93
Effort Expectancy	5	0.89
Social Influence	5	0.82
Facilitating Conditions	5	0.80
Hedonic Motivation	5	0.91
Price Value	5	0.77
Habit	5	0.77
Behavioral Intention	6	0.90
Use Behaviour	7	0.93
Ethical Concern	10	0.87
Mitigation Measures	10	0.96
Combined Ethical Concerns and Mitigation	20	0.91
Challenges	15	0.89

3.9 Ethical Consideration

Ethical considerations in research involve a set of principles designed to protect the rights, privacy, and welfare of participants through practices such as obtaining informed consent, ensuring confidentiality, and minimising potential harm, all of which are essential for maintaining the integrity of the study (American Psychological Association [APA], 2019). All participants were given a guarantee of confidentiality and anonymity in reporting the information provided for the study. Additionally, ethical issues governing human subjects in research were strictly adhered to base on the Declaration of Helsinki of 1964 and its subsequent amendments or similar guidelines and was authorised by the Department of Integrated Science Education, University of Education, Winneba. The names of participants were not taken in the research. Secondly, the features of the questionnaires, such as ease of completion and sensitivity of the questions, were all considered. There were no biases toward any religion, race, or culture.

3.7 Data Collection Procedure

Data collection is the systematic process of gathering relevant information using standardised methods such as surveys or questionnaires, and its rigor is essential for capturing accurate and representative data (Dahal et al., 2024). In this study, data were collected using a structured questionnaire administered to pre-service integrated science teachers from Level 100 to Level 400. 300 copies of the pre-tested and validated questionnaire were printed for the main data collection. The administration of the instrument was conducted in person, and each respondent was given a copy of the instrument to complete and return in one month. After the period of data collection,300 completed questionnaires were returned, representing a 100% response rate.

3.8 Data Analysis

Data analysis involves systematically examining and interpreting collected data to uncover patterns, test hypotheses, and draw valid conclusions about the research problem (Taherdoost, 2016). The data collected through the questionnaires were processed using software such as International Business Machine Statistical Package for Social Sciences (IBMSPSS), version 27, and Smart PLS version 4.0 (Richter et al., 2022). Descriptive statistical tools such as frequencies, percentages, means, and standard deviations were employed to summarise and describe the demographic information of the participants. Data from objectives 1 were analysed using frequencies and percentages. Objective 2 was analysed using mean, standard deviations, and partial least squares structural equation modelling (PLS-SEM) to compute the behavioural intention of pre-service integrated science towards the use of generative AI in learning. Objective three of the study was analysed using means, standard deviations, and two-way multivariate analysis of variance (two-way MANOVA) where sex and level of the preservice integrated science teachers were utilised as the independent variables, while ethical concerns and mitigation measures for using generative AI for learning were the dependent variables. The final objective, which sought to examine the challenges encountered when integrating generative AI in learning, was analysed with means, standard deviation, and Kendall's coefficient of concordance were used to rank the challenges on a scale of 0, indicated by no agreement, while a value of 1 is indicated by perfect agreement.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.0 Overview

Chapter Four presents the results and discusses the findings with relevant literature. The chapter provides a detailed analysis of the data gathered from the pre-service integrated science teachers at the University of Education, Winneba (UEW). The data was analysed using both descriptive and inferential statistical methods. The descriptive statistics summarised the demographic characteristics of the participant and their responses on various constructs of the study, while the inferential statistics explore relationships and differences between variables of interest.

4.1 Descriptive Statistics for the Demographic Characteristics of the Pre-Service Integrated Science Teachers.

This section presents the demographic information of the respondents who participated in the study. Descriptive statistics such as frequencies and percentages were used to summarise data on variables including sex, age, level of study, prior knowledge of AI tools, frequency of use, and the type of environment in which the respondents grew up (urban or rural). Understanding the demographic profile of participants provides context for interpreting their responses to the main research constructs and helps in drawing relevant conclusions about the population under study.

Gender of pre-service integrated science teachers

Table 2 presents the results on the gender of the pre-service integrated science teachers who participated in the study. The results indicate that more than three-fourths (78.3%) were males, while one-fifth (21.7%) were females, the finding indicating that male pre-service integrated science teacher dominate their female counterparts.

Table 2 Sex of Pre-Service Integrated Science Teachers

Sex	Frequency	Per cent (%)
Male	235	78.3%
Female	65	21.7%
Total	300	100%

Source: Field Survey (2025)

Age category of pre-service integrated science teachers

The age distribution of the pre-service integrated science teachers is presented in Table 3. Six in every ten (61.3%) teachers were between 20 and 29 years, with a mean age of 27.61 ± 5.26 years. Also, more than one-third (37.0%) were between 30 and 49 years. It is worth noting that few (1.7%) were below 20 years.

Table 3 Age Category of Pre-Service Science Teachers

Age Categories	**Frequency**	**Percentage (%)**
Less than 20	5	1.7%
20-29	184	61.3%
30-39	108	36.0%
40-49	3	1.0%
TOTAL	300	100%

Source: Field Survey (2025) Mean = 27.61±5.26

Place of origin of pre-service integrated science teachers

Table 4 displays that more than half (54.3%) of the pre-service integrated science were from rural backgrounds, while the rest (45.7%) hail from urban areas.

Table 4 Place of Origin of Pre-Service Integrated Science

Place	Frequency	Percentage (%)
Urban	137	45.7%
Rural	163	54.3%
Total	300	100%

Source: Field Survey (2025)

Academic Level of pre-service integrated science teachers

Table 5 displays an even distribution of participants across all levels: Level 100 (25%), 200 (25%), 300 (25%), and 400 (25%). This reflects a balanced representation of students across the four years of study.

Table 5 Level of Pre-Service Integrated Science Teachers

Level	**Frequency**	**Percentage (%)**
100	75	25%
200	75	25%
300	75	25%
400	75	25%
TOTAL	300	100%

Source: Field Survey (2025)

Pre-Service Integrated Science Teachers' Utilisation of Generative AI Tools

Research question one sought to address: *"How do pre-service integrated science teachers utilise generative AI tools in their learning?"* This question was directly aligned with the first objective of the study, which was to describe pre-service integrated science teachers' utilisation of generative AI tools across multiple dimensions. In this study, utilisation was operationally defined in terms of proficiency level, devices used to access AI tools, frequency of usage, prior experience, and familiarity with specific applications. These indicators were chosen to capture not only the technical competence of pre-service integrated science teachers but also the breadth of their interaction with generative AI in academic contexts, as suggested by prior studies emphasising multidimensional approaches to technology adoption in teacher education.

To achieve this objective, the analysis was conducted using descriptive statistics, specifically frequencies and percentages (Table 6- 10) , which are well suited for summarising categorical data and highlighting patterns within a given sample.

Proficiency level of pre-service integrated science teachers on generative AI tools

The generative AI proficiency of the pre-service integrated science teachers (Table 6) shows that more than half (53%) of respondents indicated that their AI proficiency level was intermediate. On the other hand, more than one-third (34.7%) revealed that their proficiency level was basic, while a little over one in ten (12.3%) had advanced proficiency.

Table 6 Proficiency Level of Pre-Service Integrated Science Teachers

Proficiency	Frequency	Percentage (%)
Basic	104	34.7%
Intermediate	159	53.0%
Advanced	37	12.3%
Total	300	100%

Source: Field Survey (2025)

Devices used by Pre-Service Integrated Science Teachers

The most used device by pre-service integrated science teachers was a smartphone, which accounted for two-fifths (41.1%) of the respondents (Table 7). Also, more than one-third (37.3%) of the pre-service integrated science teachers use both a laptop & smartphone, while very few, which is a little more than one-tenth (13.7%), use a laptop only, with less than one-tenth (7.3%) using the combination of all three devices.

Table 7 Devices Used by Pre-Service Integrated Science Teachers

Devices	Frequency	Percentage (%)
Smartphone only	123	41.1%
Laptop and Smartphone	112	37.3%
Laptop only	41	13.7%
Laptop, Tablet, and Smartphone	22	7.3%
Tablet only	1	0.3%
Laptop and Tablet	1	0.3%
Total	300	100%

Source: Field Survey (2025)

Frequent Usage of Generative AI Tools by Pre-Service Integrated Science Teachers

Table 8 presents the results, which show that almost half (49.3%) of respondents used generative AI tools daily. Also, more than two-fifths (41.1%) used AI tools weekly, and about one in ten (9.3%) used the generative AI tools bi-weekly. Only a few proportions of the respondents (0.3) reported monthly usage. This shows that regular usage of generative AI tools was common among pre-service integrated science teachers.

Table 8 Frequent Usage of Generative AI Tools by Pre-Service Integrated Science Teachers

Frequent Usage	Frequency	Percentage (%)
Daily	148	49.3%
Weekly	123	41.1%
Bi-weekly	28	9.3%
Monthly	1	0.3%
Total	300	100%

Source: Field Survey (2025)

Prior experience with generative AI tools by pre-service integrated science teachers

The prior experience of generative AI tools among pre-service integrated science teachers shows that close to nine-tenths (88.7%) of respondents had used AI tools, while just over one-tenth (11.3%) had no experience. This indicates that prior exposure and familiarity are common among pre-service integrated science teachers (Table 9).

Table 9 Prior Experience by Pre-Service Integrated Science Teachers

Place	Frequency	Percentage (%)
Yes	266	88.7%
No	34	11.3%
Total	300	100%

Source: Field Survey (2025)

Familiarity with any generative AI tools by pre-service integrated science teachers

Table 10 shows the familiarity of pre-service integrated science with specific generative AI tools. Nearly two-thirds (62.4%) were aware of ChatGPT, with around one-tenth (16.0%) knowing Gemini. Less than one-tenth of the pre-service integrated science teachers (8.7%) were familiar with Grammarly or Scholar GPT (5.3%). Only small proportions (3.3% or less) were familiar with DALL-E, Consensus, Jenni, or all the tools.

Table 10 Generative AI Tools Used by Pre-Service Integrated Science Teachers

Generative AI Tools	Frequency	Percentage (%)
CHATGPT	187	62.4%
GEMINI	48	16.0%
GRAMMARLY	26	8.7%
SCHOLAR GPT	16	5.3%
DALL-E	10	3.3%
CONSENSUS	5	1.7%
JENNI	4	1.3%
ALL	4	1.3%
Total	300	100%

Source: Field Survey (2025)

Factors influence the behavioural intention of pre-service Integrated Science teachers to adopt Generative AI tools for learning

To examine the factors influencing the behavioural intention of pre-service Integrated Science teachers to adopt generative AI tools for learning at the University of Education, Winneba, forty-eight (48) items were developed based on the Unified Theory of Acceptance and Use of Technology (UTAUT) framework which comprised of nine dimensions: seven constructs from UTAUT, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit were analysed using SmartPLS 4.0, a robust structural equation modelling tool, to explore the interrelationships among the constructs and determine the magnitude of their influence on behavioural intention. This approach provided a comprehensive understanding of how motivational, contextual, and habitual factors collectively shape the adoption and utilization of generative AI tools in the educational context.

Descriptive Statistics for UTAUT2 Constructs

The study adopted the Unified Theory of Acceptance and Use of Technology (UTAUT 2) by Venkatesh et al. (2012). Table 10 displays the results of the constructs of the UTAUT2 model. The construct that recorded the highest mean performance expectancy (overall mean 3.90±1.13), which shows that the pre-service integrated science teachers agreed that AI tools enhance their academic performance or effectiveness. This is because the pre-service integrated science teachers agreed that generative AI tools are beneficial, help to accomplish academic tasks more quickly, are useful in learning and improve learning efficiency in integrated science, leading to academic success. Hedonic Motivation ranked second with an (overall mean 3.73±1.02), indicating that pre-service integrated science teachers agreed to enjoying using AI tools and find them interesting.

This is because the pre-service integrated science teachers agreed that they enjoy using generative AI tools and finds it interesting to explore new AI tools. They also agreed that using the AI tools is pleasant and fun and feels motivated when using AI tools for learning leading to academic success. Effort Expectancy, with an overall mean of 3.70±0.98, which shows that the pre-service integrated science teachers agreed that their interaction with generative AI tools is clear and understandable thus they find it easy to use it for academic tasks. The pre-service teachers also agreed that learning to use tools and developing skilful in the AI tools is easy which does not require a lot of mental effort. Use Behaviour ranked fourth with an overall mean of 3.70±1.06 indicates that pre-service integrated science agreed they use AI tools for academic writing. The pre-services teachers agreed that they plan to explore more generative AI tools whenever they need help with academic tasks. They also feel motivated to learn new ways to use these tools and feel more interested in learning new AI tools and would prefer courses that allow the use if AI tools for academic work. Behavioural Intention ranked fifth with an overall mean of 3.67±1.03, which shows that pre-service integrated science teachers agreed that there is a strong intention to continue using AI tools. They also agreed that they will continue using the AI tools for their learning which will improve the quality of their academic work. They also agreed that using of generative AI tools is compatible with the way they learn, thus will recommend its usage to peers, and intend to use AI tools to support their learning activities. Price Value ranked sixth with an overall mean of 3.52±1.00 which indicates that pre-service integrated science teachers agreed that AI tools are cost-worthy and effective way of improving learning. They further agreed that the benefits they obtain in using AI tools outweigh the costs thus justifying any expenses, therefore they can afford to use it regularly. With an overall mean 3.36± 0.92, Social Influence was ranked seventh which shows a moderate agreement of social influence to their decision to use generative AI. Though they moderately agreed that important people and lecturers recommend that they should use of generative AI tools, they agreed that the general perception among students is that generative AI tools are helpful hence are encouraged peers to use AI tools. Facilitating Conditions ranked eighth with an overall mean of 3.30±0.91which shows there is moderate agreement with the infrastructure and support systems in the university in terms of digital technology usage. They pre-service integrated science teachers moderately agreed that they have the resources required, including reliable internet access which will enable them use generative AI tools. They further agreed that they know it is necessary to use generative AI tools. With an overall mean of 3.17±1.04, habit ranked least which suggests that pre-service integrated science teachers, even though they use AI tools, they rated their habit of AI usage as moderate. They moderately agreed that they automatically use AI tools for learning, which makes them feel natural to using AI tools in their academic work because using AI tools has become routine for university students. Overall, pre-service integrated science teachers perceive AI tools as useful, enjoyable, and easy to use, and intend to keep using them, although institutional support and habitual use are comparatively lower.

Table 11 Unified Theory of Acceptance and Use of Technology 2

UTAUT2 CONSTRUCTS	Mean	St. Deviation
Performance Expectancy	**3.90**	**1.13**
Overall, I believe generative AI tools are beneficial to my academic success	3.96	1.18
Generative AI tools help me accomplish academic tasks more quickly	3.93	1.24
I find generative AI tools useful in learning integrated science	3.92	1.19
Using generative AI tools improves my learning efficiency	3.88	1.22
Generative AI tools enhance my academic performance	3.78	1.22
Hedonic Motivation	**3.73**	**1.02**
I enjoy using generative AI tools for academic purposes	3.85	1.14
I find it interesting to explore new AI tools for learning	3.80	1.19
The experience of using generative AI tools is pleasant	3.75	1.13
I feel motivated when I use AI tools for learning	3.71	1.18
Using generative AI tools is fun	3.54	1.13
Effort Expectancy	**3.70**	**0.98**
I find generative AI tools easy to use for academic tasks	3.86	1.16
My interaction with generative AI tools is clear and understandable	3.78	1.14
Learning to use generative AI tools is easy for me	3.71	1.12
It is easy to become skilled at using generative AI tools	3.63	1.15
Using generative AI tools does not require a lot of mental effort	3.50	1.26
Use Behaviour	**3.70**	**1.06**
I plan to explore more generative AI tools for academic use	3.78	1.18

I use AI tools whenever I need help with academic tasks	3.77	1.21
I am motivated to learn new ways to use generative AI tools effectively	3.75	1.17
I enjoy using generative AI tools for academic purposes	3.73	1.15
The more I use generative AI tools, the more interested I become	3.64	1.20
I frequently use generative AI tools in my studies	3.61	1.20
I prefer courses that allow the use of generative AI tools	3.60	1.24
Behavioural Intention	**3.67**	**1.03**
I believe generative AI tools can improve the quality of my academic work	3.72	1.17
I will continue to use generative AI tools regularly for learning	3.72	1.13
I am likely to recommend the use of generative AI tools to my peers	3.71	1.13
I intend to use generative AI tools to support my learning activities	3.66	1.20
I feel confident in using generative AI tools for academic purposes	3.66	1.10
Using generative AI tools is compatible with the way I learn	3.58	1.16
Price Value	**3.52**	**1.00**
Using generative AI tools is worth the cost	3.62	1.21
Generative AI tools are a cost-effective way of improving learning	3.57	1.20
The value I get from AI tools justifies any expenses	3.50	1.24
The benefits of using AI tools outweigh the costs	3.50	1.19
I can afford to use AI tools regularly	3.40	1.20
Social Influence	**3.36**	**0.92**

The general perception among students is that generative AI tools are helpful	3.88	1.89
My peers encourage me to use generative AI tools	3.59	1.18
People important to me think I should use generative AI tools	3.38	1.18
Lecturers recommend the use of generative AI tools	3.05	1.22
I feel social pressure to use generative AI tools in learning	2.91	1.28
Facilitating Conditions	**3.30**	**0.91**
I know it is necessary to use generative AI tools	3.59	1.13
I have the resources necessary to use generative AI tools	3.47	1.18
I have access to reliable internet to use generative AI tools	3.47	1.17
I received adequate support when I encountered difficulties using generative AI tools	3.23	1.23
The university provides technical infrastructure for using AI tools	2.73	1.35
Habit	**3.17**	**1.04**
I feel it is natural to use AI tools in my academic work	3.41	1.26
Using generative AI tools has become a routine for me	3.31	1.19
I find myself automatically using generative AI tools in my studies	3.16	1.30
I am dependent on AI tools for learning	3.05	1.28
I use AI tools without thinking about it	2.91	1.27

Source: Uthman (2025) A five-point Likert scale ranging from 1 = strongly disagree, 2 = disagree, 3 = moderately agree, 4 = agree, and 5 = strongly agree.

Assessment of the Measurement Model of the UTAUT 2 Constructs

Table 12 presents PLS-SEM results of the measurement model of the UTAUT 2 constructs used in the study. The measurement model of the UTAUT 2 constructs was assessed using the outer factor loadings, Cronbach's Alpha, Composite reliability (rho_a and rho_c) and the average variance extracted (AVE) (Hair et al., 2021). Evaluation of the factor loadings of the UTAUT 2 constructs revealed that all constructs had factor loadings greater than the threshold of 0.70, approving reliability (Hulland,1999; Hair et al., 2011). The Joreskog's (A rho_a and rho_c) composite reliability (CR) and Cronbach's alpha of the UTAUT 2 constructs recorded values for all constructs were above 0.70, satisfying the requirement for internal consistency reliability (Nunnally & Bernstein, 1994). Additionally, Average Variance Extracted (AVE) function was used to examine the convergent validity of the UTAUT 2 constructs used in the study. The UTAUT 2 constructs values exceeded the acceptable limit of 0.50, providing evidence of convergent validity by confirming that the constructs explain more than half of the variance in their indicators (Fornell & Larcker, 1981).

Table 12 Analyses from SMART PLS

Construct	Indicator	Loadings	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	AVE
Effort Expectancy	EE1	0.86	0.898	0.909	0.925	0.713
(EE)	EE2	0.881				
	EE3	0.87				
	EE4	0.891				
	EE5	0.706				
Facilitating	FC1	0.859	0.842	0.861	0.893	0.678
Conditions (FC)	FC2	0.851				
	FC3	0.731				
	FC5	0.846				
Habit (HA)	HA1	0.832	0.884	0.901	0.914	0.681
	HA2	0.761				
	HA3	0.845				
	HA4	0.836				
	HA5	0.849				
Performance	PE1	0.923	0.961	0.961	0.97	0.864
Expectancy (PE)	PE2	0.939				
	PE3	0.932				
	PE4	0.931				
	PE5	0.923				
Price Value (PV)	PV1	0.826	0.886	0.891	0.917	0.688
	PV2	0.809				
	PV3	0.785				
	PV4	0.88				

	PV5	0.845				
Social Influence (SI)	SI1	0.795	0.802	0.827	0.87	0.627
	SI2	0.863				
	SI3	0.681				
	SI5	0.817				
Behavioural Intention (BI)	BI1	0.885	0.952	0.953	0.961	0.806
	BI2	0.936				
	BI3	0.908				
	BI4	0.917				
	BI5	0.877				
	BI6	0.861				

Source: Uthman (2025) EE= effort expectancy, PE= performance expectancy, FC= facilitating conditions, SI= social influence, HA= hedonic motivation, BI= behavioural intention, CR= composite reliability, AVE= average variance extracted, VIF= variance inflation factor, CI= confidence internal

Discriminant Validity

Discriminant validity of the UTAUT 2 constructs was established using the heterotrait-monotrait (HTMT) ratio criteria proposed by Henseler et al., (2015). The HTMT is the mean value of the construct indicator correlation across constructs relative to the (geometric) mean of the average correlation for the indicators measuring the same constructs (Hair et al., 2019). The UTAUT 2 constructs used in the model achieved discriminant validity where the square root of AVE for each construct (represented on the diagonal of the correlation matrix) was greater than its correlations with other constructs (Table 13), with each HTMT ratios with less than the recommended threshold of 0.85 for all variables in the model (Hair et al., 2021).

Table 13 Discriminant Validity of Results

Constructs	BI	EE	FC	HA	PE	PV	SI
BI							
EE	0.827						
FC	0.73	0.833					
HA	0.725	0.643	0.612				
PE	0.757	0.85	0.677	0.501			
PV	0.829	0.833	0.844	0.751	0.71		
SI	0.802	0.817	0.863	0.711	0.695	0.839	

Source: Uthman (2025) EE= effort expectancy, PE= performance expectancy, FC= facilitating conditions, SI= social influence, HA= hedonic motivation, BI= behavioural intention, CR= composite reliability, AVE= average variance extracted, VIF= variance inflation factor, CI= confidence internal

Evaluation of the UTAUT 2 Structural Model

Table 14 presents the structural model indices of the UTAUT 2 constructs used in the study. Before evaluating the UTAUT 2 structural model, collinearity diagnostic test was performed to confirm the absence of multi-collinearity in the model. The results of the collinearity diagnostic test showed that the UTAUT 2 constructs recorded variance inflation factors (VIF) less than the accepted threshold of 5.0 which is consistent with the recommendations of Hair et al. (2021) that VIF values should be less or equal to five. Therefore, multi-collinearity did not inflate the UTAUT 2 constructs (Hair et al., 2021). The next structural model indices that were evaluated is the coefficient of determination (R^2) of the endogenous constructs was behavioural intention towards the adoption of generative AI in learning of integrated science. The R^2 of the UTAUT 2 model were evaluated to determine the variance in the endogenous construct (behavioural intention) explained by their respective exogenous constructs (Shmueli &

Koppius, 2011). According to Hair et al. (2017), values of that approximately 0.75, 0.50 and 0.25 represent substantial, moderated and weak respectively. The R^2 value of the behavioural intention of pre-service integrated science teachers to accept and use generative AI tools for learning was 0.74 which indicated close to substantial explanatory power of the exogenous variables on the endogenous constructs, signifying that the model accounts for a meaningful proportion of variance in the dependent variables (Cohen, 1988). The seven exogenous constructs accounted for 74% (R^2; BI = 0.74) of the variance in the behavioural intention of pre-service integrated science teachers to accept and use generative AI tools for learning of integrated science. The R^2 values of the endogenous constructs show that the UTAUT 2 model had substantial predictive power, hence, is important for explaining the behavioural intention of pre-service integrated science teachers to accept and use generative AI tools for learning integrated science at the University of Education, Winneba. Adopting Cohen's (1998) effect size criteria, the f^2 effect size of the UTAUT 2 model was evaluated to determine the changes in the R^2 value of the behavioural intention when the respective exogenous constructs were held constant (Hair et al., 2019). Cohen (1988) posited that the effect size values greater than 0.02, 0.15, and 0.35, signify small, medium and large effects. The PLS-SEM results showed that effort expectancy had small effect (f^2; EE = 0.03) on the pre-service integrated science teacher's intention to accept and use generative AI tools, facilitating conditions had no effect (f^2; FC = 0.00) on the acceptance and use , habit had small effect on their acceptance and use (f^2; HA = 0.10), while performance expectancy also had small effect (f^2; PE = 0.07) on the acceptance and use, finally price value also had a small effect (f^2; PV = 0.05) on the behavioural intention for pre-service integrated science teachers to accept and use generative AI on learning of integrated science, indicating that the predictor variables exert a practically significant influence on the outcome variables (Cohen, 1988). The results indicate at the UTAUT 2 model estimation data demonstrated good statistical significance and accuracy of pre-service integrated science teachers' acceptance and use of generative AI tools for learning (Sarstedt et al., 2020).

Table 14 Structural Model Indices of the UTAUT 2 Constructs

Relationships	Std. Beta	T-value	P-value	95%BCa confidence Interval LB	95%BCa confidence Interval UB	VIF	R^2	f^2
EE -> BI	0.19	2.89	0.00	0.05	0.32	2.10	0.74	0.03
FC -> BI	0.02	0.28	0.78	-0.09	0.13	2.87		0.00
HA -> BI	0.24	4.41	0.00	0.14	0.35	2.02		0.10
PE -> BI	0.24	4.57	0.00	0.14	0.34	2.82		0.07
PV -> BI	0.22	2.90	0.01	0.07	0.36	3.42		0.05
SI -> BI	0.10	1.60	0.11	-0.02	0.22	2.91		0.02

Source: Uthman (2025) EE= effort expectancy, PE= performance expectancy, FC= facilitating conditions, SI= social influence, HA= hedonic motivation, BI= behavioural intention, CR= composite reliability, AVE= average variance extracted, VIF= variance inflation factor, CI= confidence internal, R^2= coefficient of determinant, F^2 = effect size

Direct relationships and beta coefficients

To evaluate the statistical significance of the UTAUT 2 model, the study employed the bootstrapping procedure as recommended in structural equation modelling literature (Hair et al., 2021). This approach was applied to the sample data comprising 300 respondents. Bootstrapping is a non-parametric resampling technique that estimates the stability and precision of PLS-SEM results by repeatedly drawing subsamples from the original dataset and recalculating the model estimates (Efron & Tibshirani, 1993). In this study, a bootstrapping procedure with 5,000 resamples was performed using PLS-SEM, applying a 95% confidence interval (CI) to ensure robust statistical inference

(Hair et al., 2021). For each hypothesized relationship in the structural model, the beta coefficients (β), representing the strength and direction of the relationships, were obtained along with their corresponding t-statistics and p-values to determine statistical significance. These values indicate whether the hypothesized paths hold true within the study sample. The detailed outputs, including the estimated path coefficients, t-statistics, and confidence intervals, are presented in Table 14. The use of bootstrapping in PLS-SEM is particularly important because this method does not rely on the assumption of data normality, which is often unrealistic in behavioural research (Chin, 1998; Hair et al., 2021). By generating empirical sampling distributions of the estimates, bootstrapping enhances the reliability and robustness of the results (Henseler et al., 2009). It also provides a solid basis for hypothesis testing, as significance is assessed through the empirical distribution of the parameter estimates rather than theoretical assumptions (Hair et al., 2021). Consequently, bootstrapping strengthens the credibility of the structural model assessment and ensures that the conclusions drawn about the hypothesized relationships are statistically sound. The results of the beta coefficients showed that effort expectancy (EE) had a positive and significant effect on behavioural intention (BI: $\beta = 0.19$, $t = 2.89$, $p < 0.01$). This implies that when pre-service integrated science teachers perceive generative AI tools as easy to use, they are more inclined to adopt them for learning. This result is consistent with the UTAUT2 framework, which emphasises ease of use as an important determinant of technology adoption (Venkatesh et al., 2012). The findings also revealed that the relationship between facilitating conditions (FC) and behavioural intention was found to be statistically insignificant (BI: $\beta = 0.02$, $t = 0.28$, $p = 0.78$). This suggests that infrastructural and technical support, such as access to devices such as smartphones, laptops etc, internet connectivity, or institutional assistance, may not significantly influence pre-service integrated science teachers' intention to use generative AI in this context. Habit (HA) emerged as the strongest predictor of behavioural intention (BI: $\beta = 0.24$, $t = 4.41$, $p < 0.001$). This highlights the frequency of usage of generative AI tools, automatic usage and dependency which has become daily routine for the pre-service integrated science teachers. This finding is consistent with Brown and Venkatesh (2005), who emphasised the strong role of habit in technology adoption, especially among younger populations. The implication is that integrating AI into engaging and interactive learning tasks may significantly boost adoption among pre-service integrated science teachers. The results also showed that performance expectancy (PE) significantly influenced behavioural intention (BI: $\beta = 0.24$, $t = 4.57$, $p < 0.001$). This suggests that the pre-service integrated science teachers are motivated to adopt AI tools when they believe that these tools will enhance their academic performance and learning outcomes. This finding strongly supports Davis (1989) and Venkatesh et al. (2003), who highlighted perceived usefulness as one of the most powerful determinants of technology adoption. The study also found a significant positive relationship between price value (PV) and behavioural intention (BI: $\beta = 0.22$, $t = 2.90$, $p < 0.01$). This shows that the pre-service integrated science teachers carefully considered the balance between the costs (e.g., data usage or subscription fees) and the perceived benefits of AI tools when deciding to adopt them. This finding supports the argument of Venkatesh et al. (2012), who identified price value as a critical determinant of adoption, especially in contexts where users directly bear financial costs. Finally, the relationship between social influence (SI) and behavioural intention was not statistically significant (BI: $\beta = 0.10$, $t = 1.60$, $p = 0.11$). This indicates that peer or societal pressure does not strongly influence pre-service integrated science teachers' decision to adopt generative AI tools. In the process of data analysis, hedonic motivation and use behaviour were excluded from the final structural model. Hedonic Motivation was removed because its indicators did not meet the recommended reliability thresholds and the HTMT was above 0.80, indicating that this construct did not demonstrate sufficient measurement validity. Use Behaviour was also excluded from the model to avoid conceptual redundancy. Although it is the ultimate outcome in the Unified Theory of Acceptance and Use of Technology (UTAUT 2) framework, empirical evidence and prior literature (Venkatesh et al., 2003) indicate that Behavioural Intention serves as a strong proxy for actual usage behaviour, especially in cross-sectional research designs where longitudinal tracking of actual use is not possible. Including both constructs would have introduced multicollinearity and reduced the parsimony of the model. Therefore, retaining only Behavioural Intention provided a theoretically sound and statistically efficient approach to assessing adoption tendencies in this context, however, actual usage was measured using descriptive statistics. The results from the study suggests that students' adoption of AI at UEW is primarily self-driven, based on effort expectancy, habit, performance expectancy and price value rather than facilitating conditions.

Pre-service integrated science teachers' opinion on the ethical concerns regarding the use of Generative AI tools and their mitigation strategies

The ethical concerns and mitigation strategies in use generative AI tools among pre-service integrated science teachers is presented in the section. Means, standard deviation and two-way MANOVA was used to analyse the variables, where sex and academic level were used as the independent variables ethical concerns and mitigation measures were the dependent variables. The analyse was done to check whether pre-service integrated science teachers significantly differed in terms of sex and academic levels in their perceptions of ethical concerns and mitigation measures adopted to address them. On the issue of ethical concerns regarding the use of generative AI for academic purposes, pre-service integrated science teachers moderately agreed (overall mean = 3.01±0.81) to the concern about the ethical use of generative AI tools (Table 15). The pre-service integrated science teachers moderately agreed that using generative AI to complete assignments without understanding the content is morally questionable. Again, they moderately agreed that using AI tools without proper verification may lead to the spread of false or misleading content. Furthermore, they are worried mostly about the misuse of generated AI text without understanding its content, which may lead to spreading misleading information, privacy breaches and over dependency. Concerns about dishonesty and plagiarism are present but are also moderate.

Table 15 Ethical Concerns

Ethical Concerns	Mean	Std. Deviation
Using generative AI to complete assignments without understanding the content is morally questionable	3.21	1.12
Using AI tools without proper verification may lead to the spread of false or misleading content	3.18	1.11
I may not be aware that entering personal information in AI tools can breach privacy	3.10	1.14
There are ethical concerns about the use of AI tools to impersonate others' writing styles	3.09	1.06
Generative AI tools may cause me and other students to become overly dependent and lose problem-solving skills	3.05	1.11
Generative AI increases the risks of plagiarism when I copy answers without modification	3.00	1.06
AI-generated content may include biases or discriminatory information, raising ethical issues	3.00	1.04
I worry that the use of generative AI tools might undermine the authenticity of my academic work	2.95	1.06
I often do not understand the implications of submitting AI-generated content as my own	2.91	1.06
Using generative AI tools for completing assignments may constitute dishonesty	2.70	1.10
Overall Mean	**3.01**	**0.81**

Source: Uthman (2025) A five-point Likert scale ranging from 1 = strongly disagree, 2 = disagree, 3 = moderately agree, 4 = agree, and 5 = strongly agree.

Mitigation Measures

Table 16 presents the descriptive statistics for these mitigation measures, reporting an overall mean of 3.74 ± 1.02, which indicates a high level of agreement among pre-service integrated science teachers on their necessity of implementing such strategies. Pre-service integrated science teachers agreed on clear support for integrating digital ethics education into teacher preparation programs and called for the university to establish and communicate clear guidelines on the ethical use of AI tools. They also recommended providing training on evaluating the credibility of AI-generated content and embedding AI usage policies within course structures to promote ethical academic practices. Additionally, the pre-service integrated science agreed that employing AI-detection tools can strengthen academic integrity. Additionally, pre-service integrated science teachers agreed that role of faculty in this process, noting that explaining the consequences of unethical AI usage, promoting responsible use through education, and encouraging critical reflection can reduce overreliance on AI tools. Pre-service integrated science teachers further agreed that acknowledging or citing AI-generated content should be standard practice and recommended designing practical, application-based assessments to discourage unethical AI practices.

Table 16 Mitigation Measures

Mitigation Measures	Mean	Std. Deviation
The university should integrate digital ethics education into teacher training programme	3.84	1.21
The university should create and share clear policies on how students can ethically use AI tools	3.80	1.18
The university should provide training on evaluating the accuracy of AI-generated information	3.78	1.18
Faculty should explain the consequences of unethical AI usage to students	3.77	1.14
Educating students on the responsible use of AI tools can help reduce ethical misuse	3.72	1.20
Encouraging critical reflection can help students avoid overreliance on AI tools	3.71	1.21
Including AI usage policies in courses can promote ethical academic practices	3.70	1.13
AI-generated content should be acknowledged or cited where appropriate in student work	3.70	1.19
Designing assessments that require practical application can reduce unethical AI use	3.70	1.19
Using AI-detection tools can help enforce academic integrity policies	3.68	1.21
Overall Mean	**3.74**	**1.02**

Source: Uthman (2025) A five-point Likert scale ranging from 1 = strongly disagree, 2 = disagree, 3 = moderately agree, 4 = agree, and 5 = strongly agree.

Differences in linear combination of the ethical concerns and mitigation measures adopted by pre-service Integrated Science teachers

A two-way MANOVA was conducted to examine the linear combination of the ethical concerns and mitigation measures adopted by pre-service integrated science teachers. Table 17 and 18 shows the results from the two-way MANOVA test. The independent variables were sex and academic level, while the dependent variables were ethical concerns and mitigation measures. This approach was appropriate for exploring whether demographic characteristics significantly influence pre-service integrated science teachers' perceptions of ethical concerns and the mitigation measures adopted to address them. The assumption of homogeneity of covariance matrices was examined using Box's M Test (Johnson and Wichern,2007), which yielded Box's M = 22.55, $p = 0.42$. Since the test was not statistically significant, the assumption was satisfied, and the multivariate analysis was deemed robust (Hair et al., 2021). The multivariate analysis of variance (MANOVA) results indicated that the pre-service integrated science teachers did not differ significantly based on their sex ($p = 0.36$), level of study ($p = 0.41$), and the interaction ($p = 0.36$) between sex and level on the combined dependent variables that is ethical concerns and mitigation strategies regarding the use of generative AI tools in learning. This suggests that the male and female integrated science pre service teachers in level 100 to 400 did not significantly differ in their perceptions on the ethical concerns and mitigation strategies regarding the adoption of generative AI for learning. The Pillai's Trace values (Sex = 0.01; Level = 0.02; Sex*Level = 0.02) further confirm the lack of significant multivariate differences, reinforcing the conclusion that opinion toward ethical concerns and mitigation measures are relatively homogeneous across different demographic groups in terms of sex and academic levels (Hair et al., 2021).

These results indicate that male and female pre-service integrated science teachers, regardless of their level of study, hold similar perceptions of both ethical concerns and strategies for mitigating the risks of generative AI tools in educational contexts.

(MANOVA Assumption)

Table 17 Two-Way MANOVA and Box's M

Box's M	F	df1	df2	Sig
22.55	1.03	2	294	0.42

Table 18 Multivariate Tests Using Pillai's Trace

Effect	Pillai's Trace	df1	df2	*P*
Sex	0.01	2	294	0.36
Level	0.02			0.41
Sex*Level	0.02			0.36

Source: Uthman (2025)

Challenges pre-service integrated science teachers' encounter using generative AI tools into their learning processes

Means, standard deviation and Kendall's Coefficient of Concordance were employed to examine the degree of agreement among respondents regarding these challenges. This statistical approach not only ranked the challenges in order of significance but also revealed whether there was consensus among pre-service integrated science teachers about the difficulties they encounter. Pre-service integrated science teachers acknowledged encountering several challenges in incorporating generative AI tools into their learning. They agreed about uncertainties regarding the long-term academic impact of AI, the potential for misuse of AI tools, and the difficulty in accurately evaluating AI-generated responses. They also noted apprehension about how AI might influence future academic progression. Table 19 reports an overall mean of 3.43±0.98, indicating agreement among pre-service integrated teachers on these challenges. Pre-service integrated science teachers further agreed that some AI tools are complex and difficult to navigate, underscoring the need for adequate training on their proper use. Additionally, they moderately agreed that overreliance on AI could pose risks, such as reducing critical thinking skills and creating dependency in academic tasks. Concerns were also raised about data privacy, anxieties over the overuse of AI tools impacting academic integrity, and limited access to advanced AI tools. Moreover, pre-service integrated science teachers also moderately agreed that they felt uncertain about how to integrate AI into their daily study routines and reported feeling discouraged due to inadequate support from lecturers.

Table 2 Challenges in Integrating AI Tools into the Learning of Integrated Science

Challenges Faced in Integrating AI Tools into Learning	Mean	Std. Deviation
Uncertainties about the future impact of AI on my academic progression	3.70	1.30
Students' misuse of generative AI	3.56	1.22
Inadequate evaluation of whether AI responses are correct	3.53	1.17
Uncertainties about the future impact of AI on my academic progression	3.52	1.21
Some AI tools are complex to use	3.50	1.24
Inadequate training on how to use generative AI tools	3.49	1.30
Becoming too dependent on AI for academic tasks is risky	3.47	1.27
Relying on AI may reduce my critical thinking skills	3.46	1.35
Some AI tools are confusing to use	3.44	1.26

Ethical concerns about the credibility of AI-generated content	3.44	1.22
Limited access to high-speed internet is needed for AI tools	3.40	1.25
Anxieties about the overuse of AI tools may affect my academic integrity	3.39	1.23
Inadequate knowledge of AI tools to use for learning	3.37	1.23
Uncertainties about data privacy with the use of generative AI tools	3.36	1.16
Uncertainties about integrating AI tools into my daily study routine	3.28	1.15
I feel discouraged from using AI tools due to a lack of support from lecturers	3.26	1.27
Overall mean	**3.43**	**0.98**

Source: Uthman (2025) five-point Likert scale, 1= not a challenge, 2= slightly a challenge, 3= challenge, 4= much a challenge, and 5= very much a challenge.

Ranking of the Challenges Using Kendall's Coefficient of Concordance

The challenges pre-service integrated science teachers faced in integrating generative AI tools into their learning or academic tasks was ranked using Kendall's coefficient of concordance (W) table 20 presents the results. Students' misuse of generative AI (Mean rank = 8.54) ranked highest, followed by inadequate evaluation capacity whether AI responses are correct (Mean rank = 8.45) and Uncertainties about the future impact of AI on my academic progression (Mean rank = 8.43) which ranked 2nd and 3rd respectively. Inadequate training on how to use generative AI tools (Mean rank = 8.31) ranked 4th, some AI tools are complex to use (Mean rank= 8.26) and becoming too dependent on AI for academic tasks is risky (Mean rank = 8.23) ranked 5th and 6th respectively according to the challenges pre-service teachers faced in integrating generative AI tools into their learning. The item that ranked 7th was relaying on AI may reduce my critical thinking skills (Mean rank = 8.16), with some AI tools are confusing to use (Mean rank = 8.07) ranking 8th and ethical concerns about the credibility of AI-generated content ranking 9th in the challenges. Limited access to high-speed internet needed of AI tools (Mean rank = 7.86) ranked 10th, followed by uncertainties about data privacy with the use of generative AI tools (Mean rank = 7.79) ranked 11th then inadequate knowledge of AI tools to use for learning (Mean rank = 7.67) ranking 12th. Anxieties about the overuse of AI tools may affect my academic integrity (Mean rank = 7.64) and I feel discouraged from using AI tools due to lack of support from lecturers (Mean rank = 7.39) ranked 13th and 14th respectively, finally uncertainties about integrating AI tools into my daily study routine (Mean rank = 7.20) ranked 15th being the lowest ranked challenge pre-service face in integrating AI tools into their academic works (Uthman, 2025). The Kendall's coefficient of concordance ($W = 0.02$, $\chi^2 = 57.25$, $p = 0.001$) reflects an extremely low level of agreement among the pre-service integrated science teachers regarding the ranking of challenges associated with integrating generative AI tools into their learning. A (W) value of 0.02 is very close to zero, which indicates that the respondents' rankings were highly inconsistent and that there is substantial variation in their individual perceptions of which challenges are most critical (Gibbons, 1993). In other words, the challenges were not prioritised in a uniform way across the group.

Interestingly, despite the very low concordance, the result is statistically significant ($p = 0.001$), meaning the observed pattern of rankings is unlikely to have occurred by chance. This statistical significance is largely due to the relatively large sample size, which can make even small degrees of agreement detectable (Gibbons & Chakraborti, 2021). However, the practical interpretation remains that agreement is negligible, and therefore the significance does not imply strong consensus.

This finding suggests that pre-service integrated science teachers differ widely in the aspects they perceive as most problematic when it comes to adopting AI tools. For example, while some teachers might view technical complexity or lack of training as the main obstacle, others may place more emphasis on ethical concerns, reliability of AI-generated responses, or fear of academic misuse (Sallam, 2023; Zawacki-Richter et al., 2019). The diversity in rankings could stem from differences in personal experiences with technology, varying levels of digital literacy, prior exposure to AI tools, or differences in their expectations of AI's role in education.

The lack of strong agreement highlights the need for tailored strategies to address these challenges rather than a one-size-fits-all approach. Training programs and policy interventions should consider this variability by incorporating multiple dimensions of support, technical, pedagogical, and ethical strategies to accommodate the diverse concerns held by different individuals (UNESCO, 2023). Ultimately, this result underlines the complexity of integrating generative AI into education, as the perceived barriers are not uniformly prioritized by future educators.

Table 3 Mean Ranks and Kendall's Coefficient of Concordance

Challenges	Mean Ranks	Kendall's W[a]	Chi-Square	df	Sig.
Students' misuse of generative AI	8.54	0.02	57.25	14	0.001
Inadequate evaluation capacity whether AI responses are correct	8.45				
Uncertainties about the future impact of AI on my academic progression	8.43				
Inadequate training on how to use generative AI tools	8.31				
Some AI tools are complex to use	8.26				
Becoming too dependent on AI for academic tasks is risky	8.23				
Relaying on AI may reduce my critical thinking skills	8.16				
Some AI tools are confusing to use	8.07				
Ethical concerns about the credibility of AI-generated content	8.01				
Limited access to high-speed internet needed of AI tools	7.86				

Uncertainties about data privacy with the use of generative AI tools	7.79
Inadequate knowledge of AI tools to use for learning	7.67
Anxieties about the overuse of AI tools may affect my academic integrity	7.64
I feel discouraged from using AI tools due to lack of support from lecturers	7.39
Uncertainties about integrating AI tools into my daily study routine	7.20

Source: Uthman (2025) W[a]. *Kendall's Coefficient of Concordance*

4.2 Discussion of Finding

Utilisation of Generative AI Tools by Pre-Service Integrated Science Teachers

The findings of the study revealed that the majority of pre-service integrated science teachers rated their proficiency with generative AI tools at an intermediate level (53%), with a considerable number at the basic stage (34.7%), and only a small fraction (12.3%) reporting advanced proficiency. This distribution suggests that while pre-service integrated science teachers have developed some competence in using generative AI tools, there remains a substantial gap in terms of mastery. Similar trends have been highlighted in earlier studies, which found that most students often possess moderate digital literacy but lack the depth of expertise required for advanced applications of emerging technologies (Alvarez-Risco et al., 2023; Dwivedi et al., 2023). The implication is that although the pre-service integrated science teachers are actively engaging with AI, deliberate training programs and structured exposure may be necessary to advance their skills beyond intermediate proficiency.

In terms of device usage, smartphones were the most commonly used device (41.1%), followed by the combination of laptop and smartphone (37.3%), and to a lesser extent, laptop-only users (13.7%). The dominance of smartphones reflects their affordability, accessibility, and flexibility, particularly within educational contexts in developing countries (Adu-Gyamfi et al., 2022). However, the relatively lower reliance on laptops and tablets suggests that some advanced functionalities of AI tools, which require larger interfaces or higher processing power, may not be fully explored by many pre-service integrated science teachers. This could potentially constrain the depth of integration of AI tools into academic activities. It also indicates that institutional support, in terms of infrastructure and access to diverse digital devices, may enhance the scope of utilisation (Dwivedi et al., 2019).

The frequency of usage further confirms the growing integration of generative AI in learning activities. Almost half of the respondents (49.3%) reported daily use, while another 41.1% engaged weekly. This demonstrates a high level of consistency in AI adoption, with very few respondents using AI bi-weekly (9.3%) or monthly (0.3%). These results resonate with earlier studies showing that regular and sustained use of AI tools correlates strongly with digital adoption and technology acceptance (Tamilmani et al., 2021; Venkatesh et al., 2012). The daily and weekly use patterns reflect that generative AI tools have become embedded in the academic practices of pre-service integrated science teachers, supporting them in tasks such as writing, problem-solving, and information retrieval (Kasneci et al., 2023).

The study also showed that nearly nine out of ten respondents (88.7%) had prior experience with generative AI tools, while only 11.3% reported no prior exposure. This high level of prior experience is significant, as it suggests that generative AI has already gained substantial traction among pre-service integrated science teachers. Prior experience has consistently been shown to positively influence technology acceptance, proficiency, and confidence in usage (Marikyan et al., 2022; Dwivedi et al., 2019). Therefore, the widespread prior exposure in this study is likely to enhance the willingness of pre-service integrated science teachers to integrate AI into their learning processes.

In terms of familiarity with specific generative AI tools, ChatGPT was by far the most dominant, with almost two-thirds (62.4%) of respondents indicating awareness, while other tools such as Gemini (16.0%), Grammarly (8.7%), and Scholar GPT (5.3%) were less frequently mentioned. Awareness of tools such as DALL-E, Consensus, and Jenni was minimal. This indicates that the adoption of generative AI among pre-service integrated science teachers is highly concentrated around ChatGPT, with limited exploration of other available platforms. This trend aligns with global usage patterns where ChatGPT has become the most popular and accessible AI platform for students due to its conversational interface and ease of application across academic tasks (Kasneci et al., 2023). However, the narrow familiarity profile raises concerns about over-reliance on a single platform, which could limit exposure to the broader spectrum of AI tools designed for specialised educational tasks such as research synthesis, image generation, or academic writing (Dwivedi et al., 2023).

Taken together, the findings under this objective suggest that pre-service integrated science teachers are active users of generative AI tools, with regular usage patterns and significant prior exposure. Their utilisation is, however, characterised by intermediate proficiency, dominance of smartphones, and heavy concentration on a single tool (ChatGPT). These patterns highlight both opportunities and challenges, while the consistent engagement and prior experience signal readiness for deeper AI integration in education, the gaps in advanced proficiency and limited awareness of alternative tools underscore the need for targeted training programs, institutional support, and curriculum integration to ensure balanced and effective utilisation of generative AI technologies in teacher education. In relation to the first research question, which sought to describe how pre-service integrated science teachers utilise generative AI tools in learning, the findings clearly show that their engagement is marked by intermediate proficiency, high frequency of use, widespread prior exposure, and a strong reliance on smartphones as the main access device. However, the concentration of familiarity around ChatGPT and the limited awareness of other generative AI platforms suggest that utilisation is still narrow in scope. These outcomes directly address the research objective by providing a comprehensive picture of how generative

AI tools are currently being adopted, while also highlighting areas where support and training may be required to broaden and deepen their use in teacher education.

Behavioural intention to adopt Generative AI Tools for learning

The study sought to examine the pre-service integrated science teacher's behavioural intention towards the acceptance and use of technology and the extent of generative AI usage among them utilising Unified Theory of Acceptance and Use of Technology 2 which has been used to understand the reason why people accept and use new technology (Venkatesh et al., 2012) demonstrating its effectiveness in predicting the adoption of digital technologies in the educational sector. The findings of the study provide important insights into the determinants of pre-service integrated science teachers' adoption of generative AI tools within the framework of UTAUT2. The results indicated that intrinsic factors such as effort expectancy and performance expectancy outweigh facilitating conditions or social influence in shaping students' intentions. This aligns with the argument of Venkatesh et al. (2012), who emphasised that performance expectancy and hedonic motivation are among the most consistent predictors of technology acceptance. The strong role of habit in this study resonates with Brown and Venkatesh (2005), who found that generative AI tools has become a particularly powerful driver among younger populations and in contexts where technology is novel. Similarly, a recent study by Alalwan et al. (2017) on mobile banking adoption highlighted that intrinsic enjoyment factors often outweigh perceived risks. Applied to generative AI, this suggests that students' curiosity and the pleasure of exploring new tools may stimulate adoption even more strongly than practical benefits. The significant influence of performance expectancy echoes decades of research on the Technology Acceptance Model (TAM) and UTAUT frameworks. For example, Davis (1989) and later Venkatesh et al. (2003) established perceived usefulness as the single most important determinant of adoption. In the context of education, this finding is consistent with studies such as Teo (2011), who showed that students' perception of technology's ability to improve learning outcomes directly affects their willingness to adopt it. Similar findings have also been reported in educational contexts, where perceived academic benefits drive adoption (Luckin et al., 2018). For pre-service integrated science teachers, this means that demonstrating the academic relevance of generative AI tools can play a critical role in encouraging adoption and also the belief that generative AI tools will enhance their learning outcomes significantly drives their intention to adopt it. The influence of price value is also notable. Venkatesh et al. (2012) described Price Value as critical in contexts where financial costs are directly borne by the user. In the present study, its significance highlights that students carefully weigh the benefits of AI tools against associated costs such as data or subscriptions. This mirrors findings in e-learning adoption research (Escobar-Rodríguez & Monge-Lozano, 2012), where affordability was a critical determinant of student adoption. Ensuring cost-effective or subsidised access to AI tools could therefore enhance adoption rates among pre-service integrated science teachers. However, facilitating conditions and social influence were not significant in this study. While UTAUT 2 traditionally positions these constructs as predictors of technology use, similar results have been reported in studies where students already possess high levels of digital literacy and access to resources. For example, Chao (2019) found that facilitating conditions had a limited role in university contexts where infrastructural support was abundant. Similarly, Al-Saedi et al. (2020) showed that social influence is weaker in individualistic contexts where personal motivation outweighs peer pressure. The current findings suggest that pre-service integrated science teachers at UEW rely more on self-motivation than external cues. Taken together, these findings suggest that effective strategies to promote AI adoption among pre-service integrated science teachers should focus less on infrastructural provisions and more on enhancing perceived usefulness, affordability, and the enjoyable aspects of AI use. Programs that showcase real learning benefits while also presenting AI as engaging and interactive may achieve the strongest uptake. Furthermore, policies that reduce the financial burden of accessing AI tools could significantly encourage adoption. The reliability and validity assessments indicate that the measurement model used in this study is robust. The high indicator loadings and CR values demonstrate that the items were consistent and accurately measured their respective constructs, which is critical for ensuring the reliability of the findings. The AVE values confirmed that the constructs captured a substantial portion of variance from their indicators, strengthening confidence in the convergent validity of the model.

Furthermore, the establishment of discriminant validity implies that each construct, such as performance expectancy, effort expectancy, social influence, and facilitating conditions, was empirically distinct. This is important in the context of pre-service integrated science teachers' intention to adopt generative AI tools because it shows that these constructs are not overlapping conceptually but represent unique dimensions influencing adoption behaviour. The absence of multicollinearity, as indicated by VIF values, ensures that the relationships among predictors are not biased due to redundancy, which adds credibility to the structural model outcomes. The moderate R^2 value suggests that while the model explains a substantial portion of variance in behavioural intention, other factors beyond those examined may also contribute to adoption decisions. Medium f^2 values highlight that the predictor variables, such as perceived usefulness and facilitating conditions, have meaningful effects on intention, rather than trivial ones. Furthermore, the statistical significance of most hypothesized paths ($p < 0.05$) reinforces the theoretical propositions of the Unified Theory of Acceptance and Use of Technology (UTAUT 2) in the context of generative AI adoption in teacher education. These results underscore the importance of ensuring adequate support systems, perceived ease of use, and positive expectations about performance outcomes to enhance future integration of AI tools in teacher training programs. The results of this study provide substantial support for the research objectives and the hypothesized relationships under the UTAUT framework. The second objective which is "to identify the factors influencing pre-service integrated science teachers' behavioural intention to adopt generative AI tools" was achieved, as constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions were found to have significant and meaningful effects.

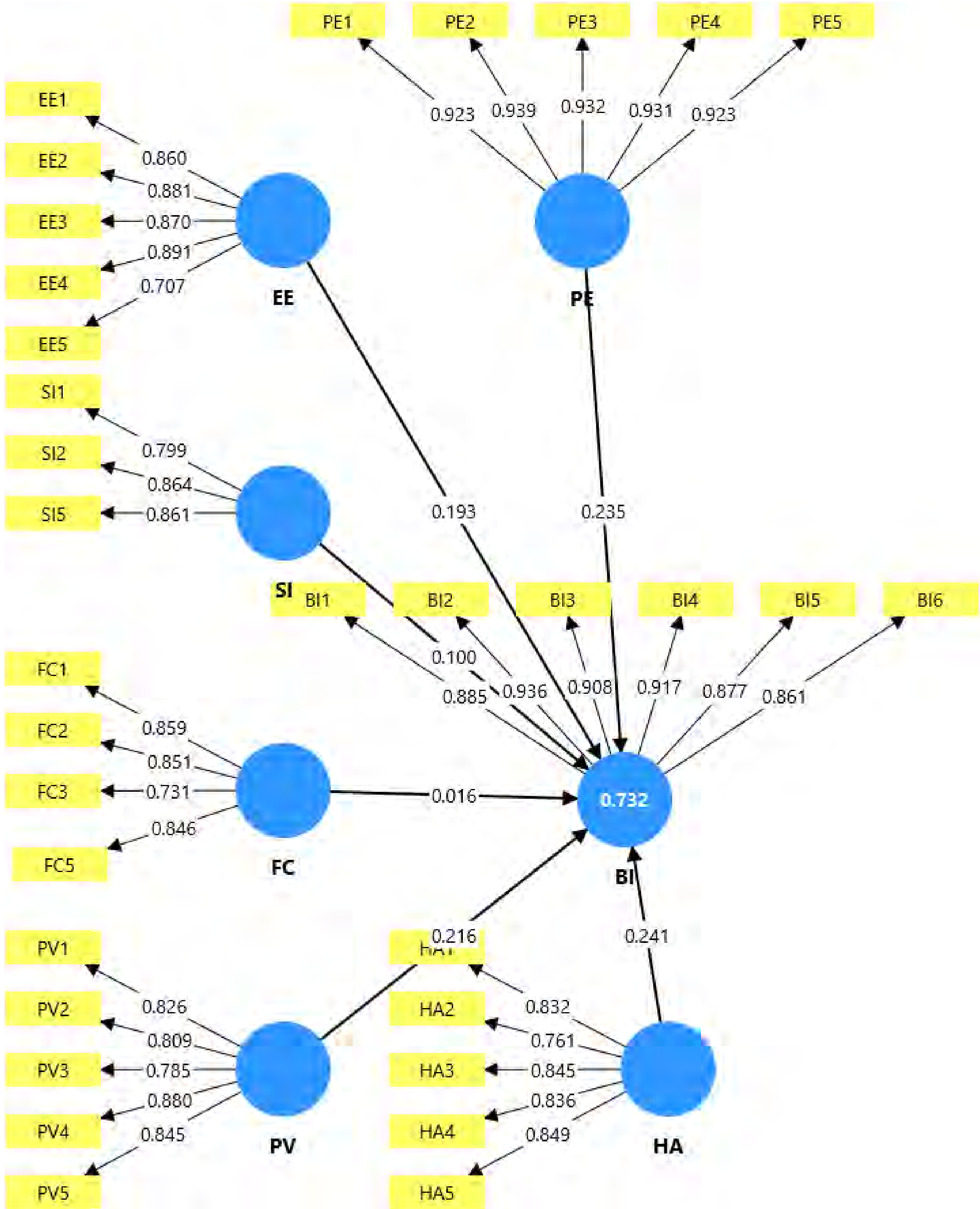

Figure 2: UTAUT 2 Model of pre-service integrated science teachers' acceptance and use of generative AI tools for learning.

Ethical Concerns and Mitigation Strategies Adopted

Descriptive statistics shows an overall mean of the ethical concerns and mitigation measures of (Mean= 3.01± 0.81) and (mean= 3.74±1.02) respectively indicating moderate concern about the ethical use of generative AI tools however, a high agreement that mitigation strategies are necessary. An inferential statistic was done using two-way multivariate analysis of variance (two-way MANOVA) where sex and level of the pre-service integrated science teachers were utilised as the independent variables, while ethical concerns and mitigation measures for using generative AI. The results from the two-way MANOVA revealed that neither sex ($p = 0.36$), academic level ($p = 0.41$), nor their interaction ($p = 0.36$) produced statistically significant differences on the combined dependent variables of ethical concerns and mitigation measures. These findings indicate that pre-service integrated science teachers' ethical perceptions regarding generative AI tools are broadly consistent across demographic categories. This result aligns with emerging empirical evidence suggesting that demographic factors play a limited role in shaping ethical orientations toward AI adoption in education (Viberg et al., 2023; Ahiatrogah et al., 2024). Viberg et al. (2023), for example, found that gender and study level did not significantly influence teachers' trust in AI systems or their ethical perceptions. Instead, AI literacy and self-efficacy emerged as stronger predictors of ethical awareness and acceptance of AI tools in educational contexts. Likewise, Ahiatrogah et al. (2024) reported similar trends among Ghanaian pre-service teachers, noting that while demographic differences affected usage frequency, they did not significantly influence ethical attitudes toward AI integration. These patterns underscore a critical insight which is ethical concerns surrounding AI are shared broadly rather than being segmented along demographic lines. The uniformity observed in this study may stem from shared institutional environments and curriculum structures that promote common ethical orientations. Pre-service teachers in the same programme often undergo similar coursework and exposure to digital technologies, fostering homogeneity in perceptions. Ethics education, often embedded in teacher preparation programs, also tends to emphasise universal principles such as fairness, transparency, and integrity, which likely contribute to this consistency. Moreover, at the pre-service level, individuals are at an early stage of professional identity formation, where attitudes tend to converge around institutional norms rather than diverge based on personal characteristics (Ko et al., 2025).

However, the lack of demographic differences should not be interpreted as an absence of ethical concerns. On the contrary, the literature indicated that pre-service integrated science teachers consistently express apprehensions regarding plagiarism, overdependence on AI, accuracy of AI-generated responses, and potential misuse in academic contexts (Bae et al., 2024; Lee & Zhai, 2024). For instance, Lee and Zhai (2024) documented frequent concerns among pre-service elementary teachers about overreliance on ChatGPT for lesson planning, fearing it could undermine creativity and critical thinking. Similarly, Bae et al. (2024) found that pre-service teachers recognized ChatGPT's potential benefits but remained cautious about its reliability and ethical implications, particularly around academic dishonesty. These findings mirror observations in the current study, where participants acknowledged the dual nature of AI tools, offering efficiency and innovation while raising questions of integrity and accountability. Wider scholarly discourse emphasises that generative AI introduces systemic ethical challenges, including algorithmic bias, privacy violations, intellectual property disputes, and misinformation risks (García-López, 2025; Dwivedi et al., 2024). These risks extend beyond individual users to institutional and societal levels, potentially reinforcing inequalities and eroding trust in educational systems. To address these concerns, Dwivedi et al. (2024) argue for robust ethical frameworks grounded in principles such as transparency, fairness, accountability, and human oversight, principles echoed in UNESCO's AI in Education recommendations. Yet, implementation remains uneven across teacher education programs, with gaps in policy coherence and practical training (Ko et al., 2025). From a theoretical perspective, these findings can also be interpreted through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT 2), which formed the conceptual foundation of this study. UTAUT 2 posits that constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions influence technology adoption (Venkatesh et al., 2012). Ethical concerns intersect with these constructs in nuanced ways. For example, perceived risks related to plagiarism and accuracy may diminish performance expectancy, while institutional policies that provide clear ethical guidelines function as facilitating conditions, enhancing trust and acceptance. The absence of demographic effects suggests that these UTAUT 2 constructs, rather than sex or level, may exert stronger influence on behavioural intention, particularly when ethical considerations are foregrounded. The implications for teacher education programs are significant. First, since ethical concerns are consistent across demographic categories, interventions can be designed at the cohort level without tailoring by sex or academic level. However, given the literature's emphasis on AI literacy as a key determinant of ethical engagement (Ko et al., 2025; Viberg et al., 2023), training should prioritize developing critical AI competencies. This includes understanding AI's technical limitations, recognizing algorithmic biases, and evaluating the reliability of AI-generated content. Incorporating ethics-focused modules into existing educational technology courses could provide a structured space for these discussions. Scenario-based learning and reflective exercises can further deepen pre-service teachers' ability to anticipate ethical dilemmas and apply mitigation strategies in practice. Second, policy-level interventions are essential to ensure that ethical principles are not left to individual discretion but institutionalized within teacher preparation frameworks. As Dwivedi et al. (2024) recommend, universities should adopt clear guidelines for responsible AI use, aligned with international best practices such as UNESCO's AI ethics recommendations. These guidelines should articulate standards for transparency, academic integrity, and data privacy, providing both pre-service teachers and faculty with a reference for ethical decision-making. Finally, the findings highlight the importance of fostering a culture of accountability and continuous dialogue on AI ethics within teacher education. As generative AI evolves, so too will its implications for teaching and learning. Ongoing research, policy refinement, and capacity-building initiatives will be critical to ensuring that educators can harness AI's benefits while safeguarding ethical and pedagogical standards. In conclusion, the absence of significant demographic differences reinforces the need for universal, systemic strategies to address ethical concerns related to generative AI in teacher education. These strategies should integrate ethical theory, AI literacy, and institutional policy to equip pre-service integrated science teachers with the knowledge and judgment required for responsible AI integration. Addressing these needs is not only a matter of technological competence but of professional ethics, central to the mission of preparing educators who can navigate the complexities of 21st-century classrooms with integrity and confidence. Or learning were the dependent variables to describe the relationships between variables.

Challenges Influencing Pre-service Integrated Science Teachers Willingness to Integrate Generative AI Tools into their Learning

Pre-service integrated science teachers reported several challenges hindering their full integration of AI tools, including uncertainties about future impacts, possible misuse by peers, inadequate training opportunities, and poor evaluation skills. The descriptive analysis showed an overall mean of 3.43 ± 0.98, indicating that there is a level of agreement among pre-service teachers that these issues are significant barriers to the effective use of generative AI in their learning. These findings are in line with Awidi and Paynter (2019), who found that insufficient institutional support and limited training continue to act as obstacles to the adoption of innovative technologies in higher education contexts. Similarly, Zawacki-Richter et al. (2019) highlighted that the lack of structured professional development is one of the key reasons educators often struggle to adopt AI tools effectively in their practice. Taken together, these results suggest that the challenges observed among pre-service integrated science teachers in Ghana are not isolated but reflect broader global patterns in AI adoption across educational systems. Despite this agreement on the presence of barriers, Kendall's coefficient of concordance ($W = 0.02$, $\chi^2 = 57.25$, $p = 0.001$) revealed a very low level of agreement on the ranking of these challenges. This indicates that while pre-service integrated science teachers largely recognise the existence of multiple barriers, they differ significantly in which ones they perceive as most pressing. Such variation suggests that teachers' prioritisation is shaped by their personal experiences, differing levels of digital literacy, and diverse exposure to AI tools (Holmes et al., 2021). For example, those with minimal exposure to AI may consider technical complexity and limited institutional training to be the most urgent concerns, while others who are more confident in their digital abilities may be more concerned with ethical issues such as plagiarism, reliability of AI outputs, and responsible use in academic settings. This observation echoes previous scholarship that emphasises how technology integration is shaped not only by institutional readiness but also by individual teacher identities, pedagogical values, and confidence in applying technology meaningfully (Tondeur et al., 2017; Lund & Wang, 2023).

These insights align with the Technological Pedagogical Content Knowledge (TPACK) framework, which underscores that effective technology integration depends on a balanced intersection of content knowledge, pedagogical strategies, and technological competence (Mishra & Koehler, 2006). For pre-service integrated science teachers, this means that AI adoption will be meaningful only if they develop not just technical skills but also the ability to align AI tools with scientific content and inquiry-based pedagogy. Where this balance is lacking, teachers may feel overwhelmed by technical barriers or may adopt AI in ways that fail to support deeper learning outcomes. Similarly, the variation in how pre-service integrated science teachers rank the challenges resonates with the Substitution–Augmentation–Modification–Redefinition (SAMR) model, which describes different levels of technology integration (Puentedura, 2014). Some pre-service integrated science teachers may only see AI as a substitute or augmentation of traditional tools, which makes training and infrastructure their primary concerns, while others who view AI as capable of redefining learning tasks may be more focused on ethical, critical, and evaluative challenges. Recognising this spectrum is crucial, as it shows that pre-service integrated science teachers are at different points in their integration journey, and support mechanisms must reflect this diversity. This diversity of perspectives reinforces the idea that interventions should not assume uniformity among pre-service integrated science teachers but instead account for their heterogeneous needs. A standardised "one-size-fits-all" approach may fail to address the fact that some pre-service teachers require foundational technical training, others need targeted guidance on pedagogical application, and still others need more advanced preparation to handle ethical and critical digital literacy challenges (Lockey et al., 2021; Souza, 2024). Policies and institutional support should therefore be flexible and layered, allowing pre-service teachers to access differentiated forms of professional development that match their readiness levels and professional contexts. This will also prevent the misallocation of resources where efforts are concentrated on a single challenge while neglecting others that different groups of teachers may find more pressing.

The findings ultimately underscore the importance of holistic and differentiated support strategies. The University of Education, Winneba (UEW) should prioritise targeted professional development initiatives that simultaneously build teachers' digital competence, strengthen steady internet and technological infrastructure, and provide opportunities for continuous mentoring. Evidence suggests that sustainable technology integration is highly dependent not only on access to tools but also on supportive professional communities and reflective practices that allow teachers to critically evaluate their use of new technologies (Lockey et al., 2016; Tondeur et al., 2017). When combined with frameworks like TPACK and SAMR, these findings make clear that preparing pre-service integrated science teachers for meaningful AI integration requires addressing both the technical and human dimensions of technology adoption. By fostering such a comprehensive approach, UEW can empower its future science teachers not merely to adopt AI tools but to transform their pedagogical practices, ensuring that AI is used responsibly to enhance creativity, inquiry, and ethical engagement in science education These conclusions also resonate strongly with Ghana's national educational policies. The Ministry of Education's ICT in Education

Policy emphasises the integration of digital technologies into teacher education programs to prepare future teachers for the demands of a knowledge-driven economy (Ministry of Education, 2018). Similarly, Ghana's Education Strategic Plan (2018–2030) highlights digital literacy and innovative pedagogy as key competencies for pre-service teachers (MoE, 2018). The challenges identified in this study demonstrate that while policy frameworks already recognise the importance of digital transformation, implementation gaps remain in areas such as infrastructure, training, and ongoing professional support. Addressing these gaps will ensure that AI adoption does not intensify inequalities but instead supports Ghana's broader vision of equipping teachers and learners with the skills necessary for the Fourth Industrial Revolution.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Overview

Chapter five presents the summary, conclusions and recommendations of the study on the factors influencing pre-service integrated science teachers' acceptance and use of generative AI tools for learning at the University of Education, Winneba. It synthesises the preceding chapters by providing a summary of the study, highlighting key findings, drawing conclusions, and making recommendations. Additionally, it outlines the contribution of the study to the body knowledge on adoption of AI for academic purposes and recommendations for further research. The chapter seeks to connect the study's objectives with the outcomes derived from data analyses, thereby providing a holistic view of the research problem and its implications for policy and practice in the University of Education, Winneba.

5.1 Summary of the Study

The study examined the factors influencing pre-service integrated science teachers' acceptance and use of generative AI tools for learning at the University of Education, Winneba. Generative AI applications such as ChatGPT and Google Bard have the potential to enhance teaching and learning through personalised support and interactive experiences, yet their adoption also raises ethical and pedagogical concerns. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT2), the study investigated the determinants of behavioural intention and actual usage. A descriptive survey design was employed, with data collected from a randomly selected sample of level 100–400 pre-service integrated science teachers. Quantitative analysis incorporating descriptive and inferential statistics, together with reliability tests, was undertaken. The findings revealed a strong willingness to adopt generative AI tools, shaped largely by performance expectancy, effort expectancy, social influence and facilitating conditions, although actual utilisation was moderate. Ethical challenges such as plagiarism, alongside infrastructural limitations and inadequate institutional guidelines, were also evident. Overall, the study underscores both the promise and risks of generative AI in teacher education and calls for clear institutional policies and targeted training to support its responsible integration into learning.

5.2 Key Findings

The key findings of the study are summarised as follows:

1. The demographic data revealed that a greater proportion (78.3%) of the pre-service integrated science teachers were male with a mean age of 27.6 years, more than half (54.3%) originated from rural backgrounds.
2. More than half of the pre-service integrated science teachers demonstrated intermediate proficiency in the use of generative AI tools, particularly through smartphones and laptops. Many reported prior experiences with tools such as ChatGPT and Gemini, which were consulted on a daily to weekly basis.
3. The results of the study indicated that, effort expectancy, facilitating conditions, habits, performance expectancy, price value, and social influence accounted for 74% of the variation in the behavioural intention of the pre-service integrated science teachers to adopt AI for their learning activities.
4. Ethical concerns identified included plagiarism, misinformation, and inadequate citation practices. Mitigation strategies reported by students included cross-checking information, using plagiarism detection software, and seeking clarification from lecturers.
5. Key challenges to AI adoption included the absence of clear institutional policies, limited formal training, infrastructural constraints such as poor

internet access, and the lack of explicit ethical guidelines to regulate responsible use.

5.3 Conclusions

Based on the key findings of the study, the following conclusions are drawn:

1. The majority of pre-service integrated science teachers were male, relatively young (mean age 27.6 years), and predominantly from rural backgrounds, indicating a demographic profile that may shape their access to and use of generative AI tools.

2. Pre-service integrated science teachers possessed intermediate proficiency in AI use, largely due to their daily and weekly prior experience with ChatGPT and Gemini, particularly on smartphones and laptops.

3. Effort expectancy, facilitating conditions, habits, performance expectancy, price value, and social influence emerged as the strongest predictors of behavioural intention to adopt generative AI for learning activities.

4. Ethical concerns such as plagiarism, misinformation, and improper citation were evident, with pre-service integrated science teachers adopting strategies like cross-checking information, using plagiarism detection tools, and seeking guidance from lecturers to address these issues.

5. Significant challenges to AI adoption were identified, including the absence of institutional policies, lack of formal training, infrastructural limitations, and insufficient ethical guidelines to promote responsible usage.

5.4 Recommendations

Based on the conclusions of the study, the following recommendations and policy implications were made:

1. The department of Integrated Science Education should organise structured AI literacy training workshops for pre-service science teachers to improve their proficiency focusing ethical use of these digital tools.
2. The department of Integrated Science Education when developing curriculum for the implementation of any training programme in AI should level on AI with which are user-friendly, intuitive and accessible because of effort expectancy on behavioural intention to adopt the technology. Attention should also be paid to the habits and price value of integrating ethical AI into the learning of students.
3. The department of Integrated Science Education in developing curriculum for the ethical AI use training of students should leverage on the benefits of ethical AI by demonstrating the clear values of increased efficiency, productivity and better outcomes due to the significant impact of performance expectancy on behavioural intention among the students.
4. The department of Integrated Science Education provide the technical and organisational infrastructure by providing the necessary resources (paid subscription of AI platforms), and training facilities to supporting on-going initiatives for AI use among students.
5. Lecturers in integrated science should intentionally integrate ethical generative AI tools into teaching and assessment.
6. The University's management should promulgate clear institutional policies and ethical guidelines on the use of generative AI tools in academic work due to the

lacked of formal guidelines on the use of unethical AI which constitute academic misconduct.

7. The department of Integrated Science Education organise a training workshop for students on handling ethical issues including plagiarism, misinformation, and fabricated references to improve the use of ethical AI among pre-service integrated science teachers for them to have a responsible future in classroom.

5.5Contribution of the Study to Knowledge

1. This study makes important contributions to knowledge in the field of science education, technology adoption, and the emerging use of generative AI in higher education. From theoretical perspective, it provides evidence on the UTAUT 2 framework in the context of Generative AI in science teacher education. While UTAUT 2 has been widely applied to other digital technologies, this study demonstrates its relevance in understanding how constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habits shape pre-service science teachers' behavioural intentions towards adopting AI tools. In addition, the findings highlight that ethical concerns such as plagiarism, misinformation, and AI bias are not peripheral but central to adoption decisions. This expends the theoretical scope of UTAUT 2 by showing that ethical concerns must be integrated into models of technology acceptance in education.
2. The study also makes significant empirical contributions because much of the literature on generative AI in education originates from technologically advanced contexts, and little is known about its use in African settings, particularly Ghana. By focusing on pre-service integrated science teachers at the University of Education, Winneba, the study provides context-specific

evidence from a developing country where infrastructural gaps, limited digital literacy, and unclear institutional policies affect AI adoption. It documents the ways in which these students use AI tools in their academic work, the challenges they face, and the strategies they adopt to address ethical dilemmas. This empirical evidence enriches the global discourse on AI in education by incorporating perspectives from underrepresented contexts.

3. In practical terms, the study contributes to knowledge by offering insights that can guide institutions, policymakers, and educators. It highlights the urgent need for AI literacy training, institutional policies on ethical use, and infrastructural investments to support equitable access. These findings are not only relevant for UEW but can also inform teacher education programs across Ghana and similar contexts. Furthermore, the study underscores the importance of pre-service teachers to use AI responsibly in their own future classrooms, equipping them with the skills and awareness to balance innovation with integrity.

5.6 Areas for Further Research

The study recommends future research in the following areas:

1. This study was limited to pre-service integrated science teachers at the University of Education, Winneba. Further studies should be conducted in other departments in the Faculty of Science Education, UEW. Future studies can also explore the acceptance and use of generative AI among students of the Colleges of Education and universities across Ghana to validate these findings and to provide a broader understanding of how different institutional contexts influence students' acceptance and use of generative AI tools.

2. The present study found that students had strong behavioural intentions to adopt generative AI tools but their actual usage remained moderate due to lack of support from lecturers and digital literacy challenges. Further research could therefore investigate intervention strategies such as structured AI literacy training and examine their effect on students' extent of use and learning outcomes.
3. Ethical concerns, particularly plagiarism and misinformation, emerged as significant issues, yet most students lacked awareness of formal ethical guidelines. Future research should explore the effectiveness of embedding ethical AI education into teachers' training curricula and assess its impact on responsible AI adoption.

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APPENDICES

Appendix A: Introductory Letter

UNIVERSITY OF EDUCATION, WINNEBA
FACULTY OF SCIENCE EDUCATION
DEPARTMENT OF INTEGRATED SCIENCE EDUCATION
P. O. BOX 25, WINNEBA, GHANA
+233 (020) 2041007
iso.uew.edu.gh

Our Ref: *ISED/PG/VOL1/82*

12[th] May, 2025

TO WHOM IT MAY CONCERN

Dear Sir/Madam,

LETTER OF INTRODUCTION

I write to introduce to you, the bearer of this letter, Miss Fadila Uthman with index number 8241180002. She is a postgraduate student in the University of Education, Winneba who is reading a Master of Philosophy programme in Science Education.

As part of the requirements of the programme she is undertaking a research on the topic: ***Factors Influencing Pre-Service Integrated Science Teachers' Acceptance and Use of Generative AI Tools for Learning at the University of Education, Winneba.***

She needs your cooperation in granting her access to your institution and facilitating the collection of data for her work.

Thank you.

Yours faithfully,

Dr. Charles Kwesi Koomson
Ag. Head of Department

APPENDIX B

QUESTIONNAIRE ITEMS

Structured Questionnaire on Factors Influencing Pre-Service Integrated Science Teachers' Acceptance and Use of Generative AI Tools for Learning at University of Education, Winneba.

INTRODUCTION

Do you give your informal consent to participate in the research project? YES [ ] NO [ ]

SECTION A: DEMOGRAPHIC INFORMATION

1. Age at last birthday: ___years
2. Gender: Male [ ] Female [ ]
3. Place of origin: Urban [ ] Rural
4. Level: Level 100 [ ] Level 200 [ ] Level 300 [ ] Level 400 [ ]
5. What is your ICT proficiency level: Basic [ ] Intermediate [ ] Advanced [ ]
6. Do you own any of these devices (Tick as many as apply):
   Laptop [ ] Tablet [ ] Smartphone [ ]
7. How often do you access the internet? Frequently [ ] Weekly [ ] Bi-Weekly [ ] Monthly [ ]
8. Do you have any prior experience with generative AI tools: Yes [ ] No [ ]

   If yes, answer the next question,
9. Are you familiar with any generative AI tools (Tick as many as apply): ChatGPT [ ] DALL·E [ ] Gemini/ Google Bard [ ] Grammarly [ ] Consensus [ ] Scholar GPT [ ] Jenni AI [ ]

SECTION B: ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT 2)

All items will be measured on a 5-point Likert scale where 1= Strongly Disagree, 2= Disagree, 3= Moderately agree, 4= Agree, 5= Strongly Agree.

STATEMENT

PERFORMANCE EXPECTANCY (PE)	**1**	**2**	**3**	**4**	**5**
Using generative AI tools improves my learning efficiency.					
Generative AI tools help me accomplish academic tasks more quickly.					
Generative AI tools enhance my academic performance.					
I find generative AI tools useful in learning integrated science.					
Overall, I believe generative AI tools are beneficial to my academic success.					
EFFORT EXPECTANCY	**1**	**2**	**3**	**4**	**5**
Learning to use generative AI tools is easy for me.					
My interaction with generative AI tools is clear and understandable.					
It is easy to become skillful at using generative AI tools.					
I find generative AI tools easy to use for academic tasks.					
Using generative AI tools does not require a lot of mental effort.					
SOCIAL INFLUENCE	**1**	**2**	**3**	**4**	**5**
People important to me think I should use generative AI tools.					
My peers encourage me to use generative AI tools.					
Lecturers recommend the use of generative AI tools in learning.					
I feel social pressure to use generative AI tools in learning.					
The general perception among students is that generative AI tools are helpful.					
FACILITATING CONDITIONS	**1**	**2**	**3**	**4**	**5**
I have the resources necessary to use generative AI tools.					
I have access to reliable internet to use generative AI tools.					
I receive adequate support when I encounter difficulties using generative AI tools					
My school provides technical infrastructure for using AI tools.					
I have knowledge necessary to use generative AI tools.					
HEDONIC MOTIVATION	**1**	**2**	**3**	**4**	**5**
I enjoy using generative AI tools for academic purposes.					
Using generative AI tools is fun.					
I find it interesting to explore new AI tools for learning.					
The experience of using generative AI tools is pleasant.					
I feel motivated when I use AI tools for learning.					

PRICE VALUE	1	2	3	4	5
Using generative AI tools is worth the cost (e.g., data, time).					
The benefits of using AI tools outweigh the costs.					
I can afford to use AI tools regularly.					
Generative AI tools are cost-effective way of improving learning.					
The value I get from AI tools justifies any expenses.					
HABIT	**1**	**2**	**3**	**4**	**5**
Using generative AI tools has become a routine for me.					
I use AI tools without thinking about it.					
It feels natural to use AI tools in my academic work.					
I am dependent on AI tools for learning.					
I find myself automatically using AI tools in my studies.					
BEHAVIOURAL INTENTION	**1**	**2**	**3**	**4**	**5**
I intend to use Generative AI tools to support my learning activities.					
I am likely to recommend the use of Generative AI to my peers.					
I believe Generative AI can improve the quality of my academic work.					
I will continue to use Generative AI tools regularly for learning.					
I feel confident in using Generative AI for academic purposes.					
Using Generative AI tools is compatible with the way I learn.					
USE BEHAVIOUR	**1**	**2**	**3**	**4**	**5**
I enjoy using Generative AI tools for academic purposes.					
I frequently use generative AI tools in my studies					
I prefer courses that allow the use of Generative AI tools.					
I use AI tools whenever I need help with academic tasks					
I plan to explore more Generative AI tools for academic use.					
The more I use Generative AI tools, the more interested I become					
I am motivated to learn new ways to use Generative AI effectively.					

SECTION C: ETHICAL CONCERNS AND MITIGATION MEASURES

All items will be measured on a 5-point Likert scale where 1= Strongly Disagree, 2= Disagree, 3= Moderately Agree, 4= Agree, 5= Strongly Agree.

Ethical Concerns IN THE USE OF GENERATIVE AI TOOLS	**1**	**2**	**3**	**4**	**5**
Using generative AI tools for completing assignments may constitute dishonesty					
Generative AI increases the risks of plagiarism when I copy answers without modification					
I worry that the use of AI tools might undermine the authenticity of my academic work.					
Generative AI tools may cause myself and other students to become overly dependent and lose problem-solving skills					
There are ethical concerns about the use of AI tools to impersonate others' writing styles					
I often do not understand the implications of submitting AI-generated content as my own					
AI-generated content may include biased or discriminatory information, raising ethical issues					
Using AI tools without proper verification may lead to spread of false or misleading content					
I may not be aware that entering personal information in AI tools can breach privacy					
Using generative AI to complete assignments without understanding the content is morally questionable					
MITIGATION MEASURES FOR ETHICAL CONCERNS	**1**	**2**	**3**	**4**	**5**
Educating students on responsible use of AI tools can help reduce ethical misuse					
The University should create and share clear policies on how students can ethically use AI					
Including AI usage policies in courses can promote ethical academic practices					
Faculty should explain the consequences of unethical AI usage to students					
AI- generated content should be acknowledge or cited where appropriate in student work					
The University should provide training on evaluating the accuracy of AI-generated information					
Encouraging critical reflection can help students avoid overreliance on AI tools					
Designing assessments that require practical application can reduce unethical AI use					

Using AI-detection tools can help enforce academic integrity policies					
The University should integrate digital ethics education into teacher training programmes.					

SECTION D: CHALLENGES IN INTEGRATING GENERATIVE AI INTO LEARNING OF INTEGRATED SCIENCE

All items will be measured on a 5-point Likert scale where 1= not a challenge, 2= slightly a challenge, 3= challenge, 4= much a challenge and 5= very much a challenge.

CHALLENGES IN INTEGRATING GENERATIVE AI INTO LEARNING OF INTEGRATED SCIENCE	**1**	**2**	**3**	**4**	**5**
Inadequate training on how to use Generative AI tools.					
Some AI tools are complex to use					
Some AI tools are confusing to use					
Relying on AI may reduce my critical thinking skills.					
Becoming too dependent on AI for academic tasks is risky.					
I feel discouraged from using AI tools due to a lack of support from lecturers.					
Limited access to high-speed internet needed for AI tools.					
Inadequate knowledge of which AI tools to use for learning.					
Ethical concerns about the credibility of AI-generated content.					
Inadequate evaluation capacity whether AI responses are correct.					
Anxieties about that overuse of AI tools may affect my academic integrity.					
Uncertainties about integrating AI tools into my daily study routine.					
Uncertainties about data privacy with the use of generative AI					
Students' misuse of Generative AI.					
Uncertainties about the future impact of AI on academic progression.					

THANK YOU