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Exploring pre-service biology teachers’ intention to teach genetics using an AI intelligent tutoring-based system

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\textbf{ABSTRACT}

This study addresses the challenge of teaching genetics effectively to high school students, a topic known to be particularly challenging. Leveraging the growing importance of artificial intelligence (AI) in education, the research explores the perspectives, attitudes, and behavioral intentions of pre-service teachers regarding the integration of AI-based applications in high school genetics education. As these pre-service teachers, commonly denoted as digital natives, are expected to seamlessly integrate technology into their future classrooms in our technology-dependent society, understanding their viewpoints is crucial. The research involved 90 teacher candidates specializing in biology from Nigerian higher education institutions. Employing the Theory of Planned Behavior, survey responses were analyzed using structural equation modeling and independent sample t-test methods. The results indicate that perceived usefulness and subjective norms are significant predictors of AI use, with subjective norms strongly influencing pre-service teachers’ behavioral intentions. Notably, perceived behavioral control does not significantly predict intentions, paralleling the observation that perceived usefulness does not guarantee AI adoption. Gender differentially affects subjective norms, particularly among female pre-service teachers, while no significant gender differences are observed in other variables, suggesting comparable attitudes. The study underscores the pivotal role of attitudes and social norms in shaping pre-service teachers’ decisions regarding AI technology integration. Detailed discussions on implications, limitations, and potential future research directions are also discussed.

\section{1. Introduction}

Genetics is a scientific field that examines the resemblances (heredity) and distinctions (variations) between parents and their offspring. Its focus lies in understanding how the characteristics of individuals are inherited from their parents and continue across generations (Akinnubi et al., 2012). Recent advancements in genetics offer the promise of enhanced disease diagnosis, treatment, and prevention. As highlighted by Ozcan (2014), progress in genetics, molecular biology, and biotechnology has significantly contributed to improving human life. Genetics knowledge plays a pivotal role in advancing areas like cyber-physical systems and molecular biology, which are considered catalysts for the fourth industrial revolution (4IR) (Maynard, 2015). Given the critical importance of genetics, there is a global need for expert geneticists. Their expertise is crucial in addressing the over 10,000 human diseases and infections resulting from genetic mutations (Goy et al., 2019; World Health Organization, 2018). These mutations pose significant health challenges worldwide, and geneticists also play vital roles in DNA testing, cloning, the development of genetically modified organisms (GMOs), disease identification (Choden & Kijkuakul, 2020), genetic sequencing, and biological exploration, among other areas. In contemporary scientific
research, genetics remains a fundamental and indispensable topic (Choden & Kijkuakul, 2020; Dorjee et al., 2017).

In Nigeria, the subject of genetics is part of the curriculum for final-year biology classes in upper secondary school (K-12). Additionally, it is studied as a field of study in science, medicine, and related disciplines at the tertiary level of education (Akinnubi et al., 2012). Despite its significance, there are reports indicating that students studying science find genetics to be a challenging and intimidating topic. They often have misconceptions and difficulties grasping its concepts, considering it one of the most complex aspects of biology (Abimbola, 2015; Adelana et al., 2023a; Auwalu et al., 2014; Onowugbeda, 2020; Sakiyo & Badau, 2015). Consequently, many students tend to avoid questions related to genetics in their final examinations (Adelana et al., 2021). Studies have attributed the complexity of genetics in biology to its abstract nature (Etobro & Banjoko, 2017; Gusmalini & Wulandari, 2020; Kantahan et al., 2020; Osman et al., 2017), resulting in fewer students enrolling in genetics or related disciplines compared to other non-STEM fields (Odufuwa et al., 2022). The challenges in learning genetics are associated with several factors, including its placement late in the biology curriculum, inadequate or non-existent science laboratories, non-STEM teachers handling biology classes, ineffective teaching methods, and a lack of modern instructional technologies tailored for teaching genetics (Ajayi & Adelana, 2020; Odufuwa et al., 2022).

To address this problem, various instructional strategies have been proposed, including the use of metaphorical instruction (Musa & Bello, 2022), logical prose and concept mapping (Alabi & Abimbola, 2022), the Culturo-Techno-Contextual Approach (CTCA) (Adebayo et al., 2022), gamification (Ajanaku et al., 2019), multimedia genetics self-learning materials (Ajayi & Adelana, 2020), learning cycles, and expository strategies (Dogru-Atay & Tekkaya, 2008), as well as annotated drawing (Danmole & Lameed, 2014). Other suggestions include the use of design criteria methods (Knippels et al., 2005), multimedia resources (Starbek et al., 2010), video games (Annetta et al., 2009), and concept mapping and problem-solving approaches (Nudelma & Okechukwu, 2006). However, little to no attention has been given to the potential use of emerging technologies such as artificial intelligence (AI)-based tools for teaching and learning genetics.

AI technology constitutes a domain within computer science dedicated to designing and developing sophisticated machines capable of emulating human cognitive functions. It encompasses a spectrum of applications, such as computer programs (e.g. online platforms) and mechanized systems (e.g. robots) (Karsenti, 2019). The technology also refers to the evolution of computer systems engineered for the execution of tasks conventionally linked to human intelligence. These tasks encompass learning, reasoning, problem-solving, natural language comprehension, speech recognition, and visual perception. The primary goal of AI technology is to construct machines and systems proficient in replicating or simulating human intelligence, empowering them to analyse data, make well-informed decisions, and progressively refine their performance. According to Ertel (2018), the primary aim of AI is to comprehend intelligence and fabricate intelligent systems. In education, AI not only facilitates novel approaches to learning and teaching but also offers insights into the mechanics of learning and introduces transformative shifts in assessment methodologies (Tuomi, 2019). Consequently, diverse user-friendly AI tools have been developed to support educators and learners in educational settings (Du Boulay, 2016; Holstein et al., 2018). The global community has positioned AI prominently on political and research agendas, acknowledging its profound impact. The advent of each new technological innovation brings forth a mix of anticipation and scepticism regarding its societal and economic ramifications. Despite AI’s foundational concepts existing for decades, recent technological advancements are rapidly expanding their potential, particularly in the discipline of science education and education at large (Tuomi, 2019).
effectiveness (Chen et al., 2020a; Hwang et al., 2014, 2020c; Lin et al., 2021). ITSs typically consist of four main components: the interface module (providing the interaction platform), the domain module (which houses instructional content representation), the student module (responsible for guiding, monitoring, measuring student learning and performance, and offering feedback), and the tutor module (containing pedagogical strategies for effective teaching within the system) (Adelana & Akinyemi, 2021; Raza, 2020). Research findings corroborate the value of ITSs as supplementary aids for improving learning outcomes. Students generally perceive these systems as effective and helpful, demonstrating a readiness to engage with them for their educational benefit (Ernest, 2015; Iddrisu et al., 2019).

To address the existing challenges in teaching and learning genetics, we propose the integration of AI technology into schools. Our approach involves assessing the behavioral intention (BI) of pre-service teachers to use this technology. BI, as described by Hou et al. (2022), refers to an individual’s intention to perform a specific behavior. Recognizing the crucial role teachers play in the educational process, particularly during the introduction of innovative ideas into the education system (Ayanwale et al., 2022), we chose to focus on biology teachers in training. This choice allows us to identify and address undesirable teaching behaviors before they become entrenched during their in-service years (Tschannen-Moran et al., 1998), as pre-service teachers are still shaping their teaching identities and approaches. Numerous factors influence teachers’ BI to integrate technology into their classrooms, as highlighted by researchers like Aptyka and Großschedl (2022), Grosschedl et al. (2014), Pobiner (2016), and Sickel & Friedrichsen (2013). These factors include knowledge (Tekkaya et al., 2012), attitude (Grosschedl et al., 2014), subjective norm (Griffith & Brem, 2004), socio-demographic variables (Deniz & Borgerding, 2018), perceived behavioral control (Sanders & Ngxola, 2009), and perceived usefulness (Salman & Güven, 2021). Addressing skills gaps and fostering a collaborative attitude within teams pose significant challenges for both students and teachers, particularly in Africa (Petker & Petersen, 2017; Pitsoe & Isingoma, 2014). This underscores the importance of exploring innovative approaches to promote teamwork alongside effective technology-human interaction in the teaching and learning of genetics in schools. To comprehensively analyze the variables predicting pre-service teachers’ BI to teach genetics using AI technology, we built our theoretical framework on the Theory of Planned Behavior (TPB) (Ajzen, 1985, 1991). Expanding upon the TPB (Ajzen & Fishbein, 2005), we introduced perceived usefulness and gender as additional factors to enhance the quality of our study (Hou et al., 2022; Sun et al., 2019). Consequently, we explored attitudes towards AI (AT), subjective norm (SN), perceived behavioral control (PBC), and perceived usefulness (PU), while also examining the independent influence of gender (GN) on all these latent variables. You can find the conceptual framework representing these factors in Figure 1.

For our analysis, we utilized a survey modelled after a similar study (Aptyka & Großschedl, 2022) and employed structural equation modeling (SEM). We believe that the outcomes of this study will prompt a reconsideration of policies governing the preparation of science teachers in teacher education programs. It should also stimulate the formulation and implementation of policies aimed at training pre-service science teachers in the utilization and integration of emerging technologies like AI. This research contributes to and broadens the knowledge base of similar studies conducted in Nigeria. Our paper is structured into various sections, including an introduction, literature review, conceptual framework and hypothesis development, methodology, results, discussion, implications, and limitations of the study.

Figure 1. Theoretical framework and research hypotheses.
2. Literature review

2.1. AI technology in education

Artificial intelligence (AI) systems are technologies that can mimic human intelligence. As popular interest in AI has increased incredibly in recent times (Jatileni et al., 2023; Sanusi et al., 2023a), the technology remains an important driving force of the 21st Century because of its speed at transforming almost all human endeavors. The field of education is not exempted from the fields that are currently using AI through machine learning in developing and automating processes. Considerably, AI technology has been able to influence educational practices globally, and efforts have continually been made to ensure that it is widely integrated into all instructional processes (Kim & Kim, 2022).

Particularly, the global increase in the need for nations to educate their citizens, and the need to implement specific national policies place a huge burden on educators and also resulted in the need to look for alternatives. This led to the massive introduction of educational artificial intelligence (Song & Wang, 2020). As a result of this, diverse educational AI tools (EAIT) came into existence and have been further developed for ease of use to support educators and their learners in educational environments. ITSs are among the most commonly used forms of EAIT because they can give personalized and automated feedback to teachers and their learners (Du Boulay, 2016; Holstein et al., 2018). The widespread utilization of EAIT has led to novel interactions between teachers and students, while significantly transforming the traditional teacher-student relationships (Choi et al. 2023; Guilherme, 2019) as shown in Figure 2.

As the 21st Century advances into the 4IR, the application of AI technology has given rise to more advanced ITSs which are machines that can imitate and effectively perform the roles of a human tutor (Adelana & Akinyemi, 2021). AI in science education has also been widely used in supporting the roles of teachers as teaching and learning facilitators, guidance counselors, intelligent tutoring systems, academic evaluators, customized learning support providers, and Chatbot, among others (Cukurova et al., 2021). When AI is applied in the traditional science education classrooms, there is improvement in assessment methods as a result of instant feedback on students’ learning progress by analyzing their learning patterns (Sánchez-Prieto et al., 2020). Over the years, educational researchers have used AI technology in enhancing assessments, and improving learning support in diverse STEM subjects (D’Mello & Graesser, 2012; Hwang & Tu, 2021; Mitrovic, 1998). In 47 studies that adopted AI technology science education as reviewed by Zhai et al. (2020), it was discovered that AI technology was highly effective and a validated alternative to traditional science assessments. It was also reported that in science education where learners are expected to perform complex pedagogical tasks, AI technology was able to provide support including being able to assist learners in carrying out scientific writings using process-oriented approaches (Latifi et al., 2020; Walker, 2019; Yang, 2021).

The learning of genetics usually poses major challenges for science students in the upper K-12 in Nigerian secondary (Ajayi & Adelana, 2020). Being a unifying theme that frequently insects between many disciplines of biology and the life sciences (Corbett et al., 2010), it becomes imperative to propose the use of AI technology for remedying the challenges teachers and students face in teaching and learning the topic respectively so that the consequences of producing biological science graduates without critical knowledge of genetics could be reduced significantly. Importantly, examining pre-service science

![Figure 2. Modification in the interactions among teachers, students, and EAITs Choi et. al. (2023).](image-url)
teachers’ behavioral intention to use AI technology in teaching genetics is also important because advances in genetics are one of the underlying key areas in 21st-century science, technology, and industry; from forensic DNA analyses to diagnosing, detecting and understanding the causes of terminal diseases such as cancer. Given this, expert geneticists are required in the biological and life sciences to manage this aspect of societal life. However, research suggests that students are currently not succeeding at developing the deep understanding of genetics necessary to participate in these activities (Corbett et al., 2010; Lewis & Wood-Robinson, 2000). It is believed that preparing pre-service teachers in using AI technology by finding out their behavioral intention to use AI will assist in relevant policymaking in this regard.

2.2. Teacher education and technology training

Teacher education in Nigeria entails critical training of would-be teachers to inculcate relevant skills for content knowledge development, instructional skills and values in their respective disciplines to be effectively prepared to model, train and guide learners to acquire knowledge and skills during their in-service career years (Akinyemi et al., 2022). According to Jekayinfa et al. (2012), the teacher education programme is particularly centered on training the intended teachers in the areas of their specific discipline and also acquiring pedagogical skills in preparation for the requirements of the teaching job. As a result of the seriousness of this training, the Federal Republic of Nigeria (2014) mandated all the education faculties in Nigerian universities, and their counterparts in the colleges of education in order to churn out self-motivated, encouraged, and effective teachers who are highly creative for their jobs. It is expected that through the acquisition of these skills by teachers, they will be able to produce well-groomed and skilled citizens who are conscious of the need to contribute to the socio-economic and sustainable development of their country. Teacher training programmes are also required to ensure that teachers who would be consciously committed to the achievement of national objectives are produced for the teaching work in Nigeria (Akinyemi et al., 2022).

The Nigerian teacher training faculties also recognise the relevance of training pre-service teachers in using technology in the classroom. In most cases, there is a dedicated course that all pre-service teachers must take and pass on ICT in education (Ismail et al., 2010). Bingimlas (2009) posits that competencies in the use of technology are one of the skills expected of pre-service teachers before they graduate from their teacher education programme. These competencies which include knowledge and abilities to integrate technology in the classroom environments are preconditions for pre-service teachers’ technology integration. Therefore, teachers are expected to be skilled in the application of educational technologies vis-à-vis getting relevant knowledge of technologies used in education, the Internet, educational software, and other related technologies for educational purposes (Oladele et al., 2022; Suárez-Rodríguez et al., 2018). However, being able to integrate technology in classroom environments is not enough; teachers must also be skilled in using technology to effectively support the complex nature of teaching and learning including being able to organize an effective classroom through the use to create a modern teaching atmosphere where students are facilitated to learn (Bahcivan et al., 2019; Cuhadar, 2018; Aslan & Zhu, 2017). Therefore, for teachers to dynamically transfer knowledge using modern pedagogical approaches (Aslan & Zhu, 2017), technological competencies must blend with pedagogical competencies (Wang et al., 2021).

Ertmer & Glazewski (2012) posit that teachers preferred pedagogical approaches influence their readiness to integrate technology in their classes. While the use of technology leads to fresh requirements for the teaching work that teachers need to embrace and adhere to, a significant number of teachers remain non-venturesome in technology integration and this becomes a barrier in an attempt to meaningfully revamp the present curriculum in preparation for catering for the integration and use of emerging technologies in schools (Hu & Garimella, 2014). According to Sanusi et al. (2022), teachers need undergo training in pedagogic competency. This training will help to equip them with the skills needed to incorporate innovative pedagogies and approaches. The underlying belief is that such training will empower them to effectively introduce emerging technologies like AI using engaging methods and initiatives. Khukalenko et al. (2022), citing Ertmer et al. (1999), were able to classify barriers to teachers’ integration of technologies into their classes into external
(e.g., non-availability of IT support staff, lack of resources such as software and hardware, nonexistent or limited technology training, etc.) and internal barriers (e.g., teachers’ unwillingness and attitude towards learning, adapting and integrating emerging technology). Given this, among others, teachers base their regular use of technology on the availability of IT support staff technical staff to attend to their challenges in the course of using technology (Wozney et al., 2006). Studies have also shown that as teachers are trained, and use technology, they acquire experience with technology and can frequently and with more flexibility integrate technology into educational practices (Khușalenko et al., 2022; Wozney et al., 2006).

3. Conceptual framework and hypotheses development

In the present study, we explored factor predicting pre-service biology teachers’ behavioral intention to teach genetics using AI technology, based on extended theory of planned behavior. The predicting factors explored are attitude towards AI technology (AAI), subjective norm (SN), perceived behavioral control (PBC), and perceived usefulness (PU). We also explored the independent effect of gender on the latent variables. Figure 1 shows our generated conceptual framework and the hypotheses proposed.

3.1. Attitude towards AI (AAI)

In the context of this study, attitude describes pre-service biology teachers’ level of favorable or unfavorable appraisal of AI technology. The successful integration and use of technology in science education critically depend on teachers’ attitudes towards technology (Yuen & Ma, 2008). Earlier, the studies of Koohang (1989) and Violato et al. (1989) have demonstrated that teachers’ attitudes in addition to their knowledge and skills in technology usage are critical factors in determining their initial acceptance or rejection of technology as well as their future behavioral intention to continue using the technology (Yuen & Ma, 2008). Several recent studies have further proved the contention between attitude and behavioral intentions (Abdel-Maksoud, 2018; Asiri, 2019; Ayanwale, 2023; Hsieh, 2015; Khor & Hazen, 2017; Pan et al., 2019; Sanusi et al., 2023b; Turan et al., 2022). We, therefore, presumed that pre-service biology teachers’ attitude (acceptance or rejection) of AI technology is crucial to whether they intend to teach genetics using the technology or not using it (Deniz & Sahin, 2016; Grosschedl et al., 2014; Kilic, 2012; Smith, 2010). Given the above, pre-service biology teachers with a positive attitude towards AI technology are more likely to use the technology in teaching genetics (Hou et al., 2022). Based on the foregoing, we hypothesized that:

H1 Pre-service biology teachers’ attitude toward AI technology predicts behavioral intention to teach genetics using AI technology.

3.2. Subjective norm (SN)

Subjective norm, according to Ajzen (1991) defines an individual feeling towards using technology based significant others’ pressure. Subjective norm is usually driven by significant others, that is, those who are likely to directly or indirectly influence the behavior of an individual. Among teachers, these drivers include colleagues, students, parents and superiors (Sadaf et al., 2012), authoritative colleagues, family, friends, and superiors (Humphrey & Aime, 2014; Kilic, 2012; Siani & Yarden, 2022). Teachers tend to develop stronger intentions because of subjective norms when those around them have higher demands and expectations (Huang et al., 2020), and are therefore likely to use technology to avoid professional isolation inside their school or connect with colleagues for collaboration and support (Trust et al., 2016). This also connotes that teachers are likely to use technology and also develop an attitude towards technology based on peer influence (Tran et al., 2023). According to Aptyka & Großschedl (2022), people are more inclined to adopt a behavioral status that can strengthen their relationships with others held in esteem. Hence, the social groups that an individual identifies with are presumed to shape their attitude and perceptions (Torcello, 2016). In addition to their behavioral intentions,
pre-service biology teachers are also likely to channel their attitudes in the direction of significant others’ expectations (Arthur, 2013). Therefore, we proposed that:

- **H2** Pre-service biology teachers’ subjective norm predicts behavioral intention to teach genetics using AI technology.
- **H3** Pre-service biology teachers’ subjective norm predicts attitude towards teaching genetics using AI technology.

### 3.3. Perceived behavioral control (PBC)

According to Ajzen (1991), PBC defines the ease an individual feels during the performance of a particular task based on available resources and opportunities (i.e., someone’s estimate of the importance of the perceived facilitators) and perceived facilitators (i.e., someone’s perceptions of the available resources, capabilities, and opportunities). In the context of this study, PBC describes the extent to which pre-service biology teachers feel competent, skilled, and equipped with resources to teach genetics using AI technology. Ajzen (1991) further posits individuals are more likely to perform a behavior should they have a high level of perceived behavioral control over the behavior. In consonance with Bandura’s (1977) concept of self-efficacy, constructivist pedagogical beliefs and technology competencies are likely to influence PBC, that is, a person’s confidence in performing the behavior and the degree of control over the environment. According to Aptyka & Großschedl (2022), confident pre-service teachers with a high level of PBC over teaching genetics using AI technology are likely follow their intentions, while those with a low level of PBC are likely to have decreased behavioral intention to teach genetics using AI technology (Kilic, 2012). Since PBC is one of the factors predicting behavioral intentions, we, therefore, hypothesized that:

- **H4** Pre-service biology teachers perceived behavioral control predicts behavioral intention to teach genetics using AI technology.

### 3.4. Perceived usefulness (PU)

Perceived usefulness defines an individual’s level of belief that the use of technology will improve their task performances, thereby relieving their efforts. Within the technology acceptance model, PU enjoys wide usage in predicting behavioral intention (Davis, 1989), and as an important. Davis (1989) popularized the idea of PU when he explained that PU is the degree to which individuals believe that using a particular technology would enhance their work performance. Several reports, including those of Darmansyah et al. (2020), and Samuel et al. (2018), confirmed that PU strongly predicts the behavioral intention of AI usage, and this was further confirmed by the studies of Ayanwale et al. (2022), Aptyka & Großschedl (2022), Salman & Güven (2021), Glavee-Geo et al. (2017) and Ramayah & Ignatius (2005). Based on the foregoing, we hypothesized that:

- **H5** Pre-service biology teachers’ perceived usefulness of AI technology predicts behavioral intention to teach genetics using the technology.
- **H6** Pre-service biology teachers’ perceived usefulness of AI technology predicts attitude towards teaching genetics using AI technology.

### 3.5. Gender

Various studies (e.g. Barker & Aspray, 2006; Kay, 2008, 2009; Terzis & Economides, 2011; Wang et al., 2009) have examined gender differences concerning its effect on technology adoption. These studies have increasingly demonstrated that providing detailed information about differences in gender concerning the use of technology is vital to stakeholders in education and learning technology providers. It is presumed that by understanding the role of gender in attitudes towards technology, teachers are better positioned to learn how to improve learning processes for students based on gender (Bao et al.,
Venkatesh et al. (2003a, 2003b) suggested that gender could influence the constructs of technology adoption, for several reasons, among which is the fact that gender differences are embedded within social and cognitive instrumental processes that influence technology adoption, and that gender and the use of technology were more strongly connected with perceptions of relevance amongst males than among females (Venkatesh & Morris, 2000). In other words, the adoption of technology is more strongly linked with ease-of-use perceptions and subjective norms, although the effect of subjective norms diminished over time (Orser et al., 2012). Based on these positions, we checked for the effect of gender on each of the latent variables considered in this study.

3.6. Research model

The present study explored the factors predicting pre-service biology teachers’ behavioral intention to teach genetics using AI technology in high school science classrooms. To the best of our knowledge, there is a dearth of studies that have explored these factors as carried out in the study in Nigeria. This study becomes urgent and necessary due to the dwindling students’ representation in genetically related fields in Nigerian institutions because they were taught genetics in a way that made them find the topic hard to comprehend and lose interest in it (Odufuwa et al., 2022). We believe that our findings will assist stakeholders in science education in Nigeria to come up with policies that will adequately cater for revamping the teacher education programme in Nigeria to train their pre-service science teachers on the use of emerging technologies such as AI and prepare them to deploy the technology during their in-service classroom environments. Complementing the validated theory of planned behavior (Ajzen, 1985, 1991; Ajzen & Fishbein, 2005) with additional two variables (perceived usefulness, and gender), we explored the extent to which attitude towards AI technology, subjective norms, perceived behavioral control, perceived usefulness, predict behavioral intentions (BI) to teach genetics using AI technology. These factors have been used in other studies, for instance in Cheng (2018), Deniz & Borgerding (2018), Clement (2015), and Griffith & Brem (2004), to predict BI in another context different from the present study. The model we proposed is shown in Figure 2.

4. Methodology

4.1. Procedure and participants

In this research, participants were approached with transparency and clarity regarding the study’s objectives, procedures, and potential risks and benefits. Each participant was presented with a comprehensive consent form outlining the nature of their involvement. This document explicitly conveyed the voluntary nature of participation, assuring participants that they could withdraw from the study at any stage without facing adverse consequences. In each institution, the coordinator in-charge of the students were also involved during the training (along with the se of videos on ITSs detaining ITSs usage and viability) and data collection processes. After obtaining approvals, the training was conducted online due to the difficult nature of arranging a physical one as a result of clashes between our timetable and those of the students. timetable of the students and our own time. The consents form and data collection tools were designed using google forms and shared as a link with the students. Importantly, participants were informed that their decision to participate or withdraw would not affect their standing with the researchers or the institution. Also, to safeguard participant confidentiality and anonymity, a meticulous approach was adopted. All collected data were anonymized and coded before secure storage. Personal identifiers, such as names and contact information, were kept separate from the research data, with only the researchers accessing the key linking participants to their respective codes. Additionally, during data analysis, any potentially identifying information shared by participants was scrupulously anonymized to uphold their privacy. Importantly, ethical approval for this study was sought and obtained from the involved institutional review boards. The ethical review process involved a thorough evaluation of the study’s design, procedures, and potential impact on participants. Approval was granted based on the study’s adherence to ethical guidelines and standards, ensuring the protection of participants’ rights and well-being throughout the research journey. Ninety biology teachers, currently in their final year of
teacher training, were recruited from both a state university of education (encompassing 400-level students) and a college of education (comprising 300-level students) situated in Southwest Nigeria. There are 60 and 40 pre-service biology teachers from the university and college of education, respectively. Out of the total sample, 21.1% were male, while 78.9% were female pre-service teachers, respectively. The participants have taken a compulsory course (Educational Technology) which is mandatory for all pre-service teachers in order to be trained on effective use of technology in education as well as emerging issues on technology application in the field of education in general. It was specifically noted that the study participants had received 6-weeks training on how to use ITS to teach genetics in the classroom based on its user-friendliness and compatibility with the course content.

The six-week training initiative on the utilization of Intelligent Tutoring Systems (ITS) for teaching genetics to pre-service teachers unfolded as follows: In the initial fortnight, participants delved into the realm of Intelligent Tutoring Systems (ITS) during four-hour sessions per day. The focus was on establishing pedagogical foundations, commencing with an overview of ITS and its significance in education. Emphasis was placed on comprehending the basic functionalities of ITS interfaces. Subsequently, days 3-4, totaling 8 hours, were dedicated to delving into the pedagogical foundations, concentrating on the principles of effective teaching and learning, particularly how ITS aligns with diverse pedagogical approaches. Moving on to days 5-10, spanning 20 hours, participants engaged in hands-on exploration of ITS. Practical sessions were conducted, allowing participants to become familiar with the ITS interface, its basic functionalities, and navigation. Transitioning to weeks 3-4, participants furthered their comprehension of ITS features. A total of 4 hours was dedicated to exploring personalized learning and its implementation using ITS on days 1-2. Following this, days 3-4, covering 8 hours, were centered on how ITS adapts assessments based on student progress. Participants were actively involved in creating assessments tailored to the field of biology. Finally, days 5-10, totaling 20 hours, were allocated for practical sessions on customizing ITS settings and seamlessly integrating genetics course content into the ITS platform. In the concluding weeks 5-6, attention shifted to understanding effective teaching strategies using ITS. Four-hour sessions on days 1-2 were dedicated to discussing strategies for seamlessly integrating ITS into classroom teaching. This involved imparting knowledge on balancing traditional teaching methods with the incorporation of ITS. Days 3-4, comprising 8 hours, focused on exploring techniques to enhance student engagement using ITS. Additionally, discussions were held on addressing challenges and cultivating a positive learning environment. The concluding days 5-6, covering 8 hours, saw participants designing and delivering lessons using ITS. The week culminated in peer evaluations and constructive feedback. Throughout the six-week program, participants had access to a dedicated platform for ongoing support and discussions. This facilitated the sharing of experiences, addressing challenges, and collectively finding solutions.

Meanwhile, out of the 100 teachers with whom the instrument was shared, only 90 voluntarily responded by freely consenting to participate and thereafter filled out the instrument. The sample size represents 90% of the total population of pre-service biology teachers who voluntarily consented to participate in the study.

The teachers sampled in the study voluntarily participated after reading and agreeing to the consent-seeking information attached to the web-based instrument used in the study. The consent section of the e-instrument contains simple-to-understand information on the need for consent before participating, data protection, and confidentiality. The e-instrument was designed using Google web-based forms, which were later shared on the platforms of the pre-service teachers through their class coordinators and lecturers after obtaining the required permissions to do so. The e-instrument was left open for two months, between December 5th, 2022, and January 30th, 2023. The demographic details of the pre-service teachers are presented in Table 1.

### 4.2. Survey instrument

This study adapted an existing and validated survey instrument (Aptyka & Großschedl, 2022). After determining the specific focus of our study, a total number of seven items were adapted for Attitude towards AI (AT), three items for Perceived usefulness (PU), three items for Subjective norm (SN), two items for Perceived behavioral control (PB), and three items for Behavioral intention to teach genetics (BI). In total,
18 items were adopted in the study (see Appendix 1). The final instrument was divided into two sections with section one requesting the demographics of the pre-service teachers while section two, which was further subdivided into five units based on the constructs examined in the study, contains items based on the constructs measured. The e-instrument was then designed using Google web-based forms and structured such that the participating pre-service teachers could respond to the items without wasting time and also with the view to increasing the likelihood of completing the survey without fatigue. Section two of the instrument which contains the 16 scale items raised in the study has a seven-point Likert-scale option thus: 1 – Strongly Disagree, 2 – Disagree, 3 – Slightly Disagree, 4 – Neutral, 5 – Slightly Agree, 6 – Agree, and 7 – Strongly Agree.

### 4.3. Data analysis

We used partial least squares structural equation modeling (PLS-SEM) to test our research hypotheses, which enables quantification of group differences while accounting for possible measurement bias in constructs and examines group differences in construct relationships (Kline, 2015). We used a sequential partial regression approach for our analyses. The present study used this procedure because it is a robust procedure for PLS-SEM (Hair et al., 2011) and suits a sample size of this size. It has been established that in PLS-SEM, the minimum sample size is estimated using the ‘ten-time rule’ (Hair et al., 2011; Peng & Lai, 2012). One commonly used variation of this method is based on a rule that the sample size should be greater than 10 times the maximum number of inner or outer model links pointing at latent variables (Goodhue et al., 2012). Due to the seven outer model links pointing to a latent variable in this study, the minimum sample size required is $7 \times 10 = 70$. Using SmartPLS software version 4.0.8, two steps were used to analyze the data: the measurement model (such as factor loading, Cronbach alpha, Composite reliability, Average variance extracted, and cross-loading) and the structural model (such as relationships among constructs using path coefficients and testing their significance using bootstrapping, the explanatory power of the model using adjusted R-square and effect size), whereas multi-group analysis was used to test for gender differences in the relationships among constructs.

### 4.4. Common method bias

An emerging statistical technique, partial least squares structural equation modeling (PLS-SEM), is gaining popularity in behavioral research and social sciences. It is, however, susceptible to various types of bias, which can influence the accuracy and validity of the results (Williams & McGonagle, 2016). In PLS-SEM, common method bias (CMB), one of the most common types of bias, can occur if care is not taken. CMB occurs when data are collected on multiple constructs using the same measurement method or instrument. Rather than individual constructs, the method of measurement is responsible for the variance in the observed scores. Consequently, results and conclusions may be inaccurate since the relationships between the constructs can be overestimated or underestimated (Williams & McGonagle, 2016). PLS-SEM can also be affected by CMB in several ways. This can cause an inflated or deflated correlation between constructs, which may affect model fitting and path coefficient estimates. Also, CMB can lower the model’s predictive power and decrease the measure’s validity and reliability (Podsakoff et al., 2003). More so, CMB can be detected using several methods. The most common method is the Harman single-factor which relies on exploratory factor analysis to identify a dominant factor among all the items in the study. There may be CMB present in the data if a single factor explains a significant percentage of

<table>
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<th>Variable</th>
<th>Categories</th>
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<tbody>
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</table>
variance. A lack of sensitivity and specificity has, however, been criticized for this method (Williams & McGonagle, 2016). As suggested by Kock & Gaskins (2014); Kock & Lynn (2012), the variance inflation factor (VIF) was used in this study to establish CMB. For all latent variables and their measures, SmartPLS software generates VIFs. When a VIF exceeds 3.3, it is regarded as a sign of pathological collinearity. Additionally, it may suggest that a model is biased by common methodological factors. Therefore, a model can be considered free of common method bias if all VIFs results from a collinearity test are equal to or lower than 3.3 (Kock, 2017, 2021). In this study, the VIFs are well below the cut-off value of 3.3, which indicates no CMB (see Table 1).

5. Results

5.1. Descriptive statistics

Descriptive statistics for all the items of the construct were computed using mean and standard deviation (see Table 2).

The results reveal that the behavioral intention to teach genetics (BI) is notably high, with BI1 showing a mean of 5.522 and a low standard deviation (SD) of 1.439, indicating a consistent and strong intention among participants. Similarly, BI4 also exhibits a high mean of 5.500 and a low SD of 1.424, reafﬁrming a robust inclination to teach genetics. However, BI2, with a mean of 5.256 and a higher SD of 1.637, indicates some variability in participants’ intentions. Moving to attitudes towards AI (AT), AT1 has a high mean of 5.667, indicating a positive attitude with a low SD of 1.491, suggesting uniform agreement. AT2, with a mean of 5.389 and a higher SD of 1.768, suggests slightly more varied attitudes among participants. The remaining AT items (AT3, AT4, AT5, AT6, AT7) collectively reveal positive attitudes towards AI, with varying degrees of agreement. For subjective norm (SN), SN1 has a lower mean of 3.867, suggesting a somewhat neutral or slightly negative subjective norm. The higher SD of 1.579 indicates diverse opinions among participants. SN2 and SN3, with higher means, suggest a more positive subjective norm, though with some variability in responses. Perceived behavioral control (PB) items indicate a strong perceived control (PB1 mean: 5.222) and consistency (low SD: 1.743), while PB3 (mean: 5.100, SD: 1.713) shows a similarly high level of control but with slightly more variability. In terms of perceived usefulness (PU), PU1 has a high mean of 5.311, indicating a positive perception with a moderate SD of 1.644, suggesting some variability in responses. PU2 and PU3 collectively convey positive perceptions of usefulness with differing degrees of agreement among participants. These ﬁndings portray a generally positive disposition towards teaching genetics, a favorable attitude towards AI, and positive perceptions of subjective norm, perceived behavioral control, and perceived usefulness. The variability in responses on certain items, indicated by higher standard deviations, highlights the diversity of opinions among participants.

| Table 2. Descriptive statistics of the manifest variables. |
| Variable | Mean | SD |
| BI1 | 5.522 | 1.439 |
| BI2 | 5.256 | 1.637 |
| BI4 | 5.500 | 1.424 |
| AT1 | 5.667 | 1.491 |
| AT2 | 5.389 | 1.768 |
| AT3 | 5.300 | 1.386 |
| AT4 | 5.200 | 1.720 |
| AT5 | 5.544 | 1.521 |
| AT6 | 5.489 | 1.462 |
| AT7 | 5.544 | 1.492 |
| SN1 | 3.867 | 1.579 |
| SN2 | 5.178 | 1.710 |
| SN3 | 5.133 | 1.621 |
| PB1 | 5.222 | 1.743 |
| PB3 | 5.100 | 1.713 |
| PU1 | 5.311 | 1.644 |
| PU2 | 5.067 | 1.800 |
| PU3 | 5.556 | 1.317 |
5.2. Confirmatory composite analysis

A subset of three criteria was used to assess construct reliability and validity: indicator reliability, composite reliability (CR), Cronbach’s alpha (\(\alpha\)), and average variance extracted (AVE) (Hair et al., 2010, 2022, Molefi & Ayanwale, 2023). A factor loading of more than 0.60 is considered substantial by Adelana et al. (2023b), Bagozzi (1981), and Hair et al. (2010). Nonetheless, some manifest variables (PB2 = 0.402, SN1 = 0.207, and BI3 = 0.496) had outer loadings below 0.60 in the model, resulting in low AVE values. In this sense, items with loadings below 0.60 were considered unreliable for measuring constructs. In this regard, such items are excluded from the hypothesized model since they cannot be used to test it.

Following the removal of these items, the AVEs displayed results above 0.50. Additionally, Ayanwale et al., 2023a; Amusa & Ayanwale (2021); Anderson & Gerbing (1988); and Fornell & Larcker (1981) suggested a CR and \(\alpha\) value of 0.70 as substantial for the assessment of construct reliability. Table 1 shows that all five constructs had CR and Cronbach’s alpha values greater than 0.70, except for PB (0.670). Also, Ayanwale et al. (2022, 2023b) and Hair et al. (2010) found significant convergent validity when the AVE exceeded 0.50. Each of the five constructs’ AVE values (0.613 to 0.723) met the acceptable value, indicating convergent validity (see Table 3).

The discriminant validity of this study was determined through cross-loading, which is the correlation between items and latent variables that are not their intended targets. Specifically, cross-loadings refer to correlations between an item and another construct in the model rather than its intended construct. According to a general rule of thumb, cross-loading should be less than 0.40 to demonstrate discriminant validity. A discriminant validity assessment is supported if the item cross-loads on its intended construct more than it cross-loads on other constructs and if the magnitude of the cross-loading on other constructs is relatively low (Fornell & Larcker, 1981; Henseler et al., 2015). Table 4 illustrates how an item’s cross-loading with its desired latent variable is higher (bold values) than its cross-loading with other latent variables. As a result, we conclude that the constructs display distinctiveness from other similar constructs in the model, i.e., they exhibit discriminant validity. Overall, it was demonstrated that all constructs were reliable and valid. Thus, we were able to assess the structural model.

5.3. Structural model evaluation

As criteria for assessing the structural model, we considered structural model collinearity, size, and significance of path coefficients, \(R^2\) of endogenous variables, effect size (\(f^2\)), and predictive relevance (\(Q^2\)). Using the Variance Inflation Factor (VIF), we were able to address collinearity. When the VIF is greater than 5, there may be a collinearity problem among the constructs, as suggested by Hair et al. (2011). This study’s VIF value is less than 5, or between 1.075 and 3.290, indicating no collinearity between its latent variables. A bootstrap analysis is then conducted on 5000 subsamples and 90 cases to determine

<table>
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<tr>
<th>Manifest variable</th>
<th>Factor loading</th>
<th>(\alpha)</th>
<th>CR</th>
<th>AVE</th>
<th>VIF</th>
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<tr>
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<td>1.896</td>
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</tbody>
</table>

Note: AT: Attitude towards AI; PU: Perceived usefulness; SN: Subjective norm; PB: Perceived behavioral control; BI: Behavioral intention to teach genetics.
the size and significance of the path coefficients and t-statistics (See Table 5). As a result, the authors can test the hypothesized relationships between the constructs. The path coefficients can range between -1 and +1. A path coefficient value closer to 0, the weaker its ability to predict dependent (endogenous) constructs; a path coefficient value closer to 1, the stronger its ability to predict dependent constructs (see Table 5).

Furthermore, we calculated the coefficient of determination ($R^2$) for all endogenous constructs to determine their in-sample prediction. Models are evaluated primarily based on their explanatory ability using $R^2$. There is a possible range of 0 to 1 for the $R^2$ value. Explanatory power increases as the value increases. Those with absolute $R^2$ values close to 0.50 tend to have moderate explanatory power, while those with absolute $R^2$ values above 0.50 tend to have high explanatory power. In this study, an $R^2$ value of 0.503 for AT accounts for 50.3% of the variation observed in attitude toward teaching AI and 66.9% of the variation observed in behavioral intention to teach AI (See Table 5). As a result, the model has a moderately-high degree of explanatory power and very well explains the latent variables in this study. In addition, effect size ($f^2$) measures the magnitude of an effect regardless of the size of the sample analyzed. The effect sizes of 0.02, 0.15, and 0.35 are, according to the convention, small, medium, and large (Cohen, 1998, 1992; Kock, 2014). We found that AT -> BI has a medium-effect explanatory ability, which is indicated by the explanatory effect value $f^2$ of 0.236. It displays small-effect explanatory ability with an explanatory effect value $f^2$ of 0.060 for PB -> BI. A medium-effect explanatory ability is exhibited by the explanatory coefficient $f^2$ of PU -> AT, which is 0.210. As PU -> BI exhibits a very small explanatory ability, the explanatory effect value $f^2$ is 0.004. As a result, the explanatory effect value $f^2$ of SN -> AT is 0.273, which displays a small-effect explanatory ability, whereas the explanatory effect value $f^2$ of SN -> BI is 0.175, which displays a medium-effect explanatory ability. Except for the explanatory effect value of PB -> BI and PU -> BI, which shows a small-effect explanatory ability, the rest exhibit a medium-effect explanatory ability. As a result, exogenous variables can explain endogenous variables to
a moderate extent in the model. Further, the blindfolded method (Geisser, 1974; Stone, 1974) was also used to evaluate the predictive significance (Q2) of the model. A Q2 greater than zero value indicates predictive relevance, while a value below 0 indicates the absence of predictive value. The PLS-SEM model has a large predictive relevance when the Q2 value is greater than 0.25 (Hair et al., 2020). A large predictive relevance was indicated by the Q2 values of 0.269 and 0.328, as shown in Table 5.

As shown in Table 5, AT (β = 0.400, p = 0.002) and SN (β = 0.358, p = 0.009) have a significant positive relationship with BI. Yet, PB and PU could not predict any significant variance in BI ((β = 0.219, p = 0.064, and (β = −0.051, p = 0.323). Likewise, both PU (β = 0.380, p = 0.000) and SN (β = 0.435, p = 0.000) were able to have significant positive regression weights with AT. Accordingly, except for H2 and H4, all hypotheses H1, H3, H5, and H6 are supported. It was found that behavioral intentions to teach AI was best predicted by attitude toward the teaching of AI. Accordingly, this supports the proposition in the current study that educators with a positive attitude toward teaching AI have a higher likelihood of having a positive intention to instruct students. This result may have implications for educational programs that wish to integrate AI into their curriculum. To increase the likelihood of educators teaching AI, developing positive attitudes toward AI may be useful. Educators who are unaware of AI may also benefit from it by designing more effective training programs. Additionally, a mean difference analysis of pre-service teachers’ gender was conducted using the study’s latent variables. In this study, independent sample t-tests were performed using Jamovi software version 2.2.3 (Jamovi project, 2021). Based on the results, Table 6 is presented.

As a result of independent sample t-tests for pre-service teachers of different gender, the mean score for attitude towards AI was 37.580 for males, while a mean score of 38.280 for females was slightly higher (See Table 6). The t-test results, however, indicate that the difference between these means is not statistically significant (t = −0.316, p = 0.376), indicating that it is most likely due to chance variation rather than real differences in attitude between males and females. Therefore, the alternative hypothesis could not be supported. In this case, gender may not be a key determinant of attitudes toward the use of AI applications to teach genetics. However, it is important to note that this study only examined attitudes toward AI. Other aspects of AI may show greater gender differences. In addition, the mean perceived behavioral control score for males is 10.00, while it is slightly higher for females at 10.41. The t-value is −0.579, and the p-value is 0.282. When the t-value is negative, the mean for males is lower than the mean for females, indicating a difference between the two groups. There is no statistical significance between the means, as the p-value exceeds the conventional threshold of 0.05. As a result, the alternative hypothesis is unfounded. This finding may have different implications depending on the study’s context.

Further, pre-service teachers were assessed on their subjective norms, with male and female scores reported separately. As shown in Table 6, the mean score for females (15.610) is higher than the mean score for males (13.680). Additionally, a statistical test was conducted (t = −1.703, p = 0.046), which suggests that the difference between the means is statistically significant at a significance level of 0.05. Also, as shown in Table 5, pre-service teachers perceive the usefulness of teaching genetics using AI technology, and their perceptions differ between males and females. There is virtually no difference between male and female pre-service teachers’ perceptions of the usefulness of AI technology when teaching genetics, based on the t-value of 0.018. Due to the p-value of 0.493, there is no statistically

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Gender</th>
<th>N</th>
<th>Mean</th>
<th>Std. dev</th>
<th>Mean Diff</th>
<th>t-value</th>
<th>p-value</th>
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Note: One tail test (p < 1.65); S-Significant; NS: Non-significant; AT: Attitude toward AI; PU: Perceived usefulness; SN: Subjective norm; PB: Perceived behavioral control; BI: Behavioral intention to teach genetics.
significant difference between the groups. Therefore, the alternative hypothesis was not supported. Additionally, according to Table 6, there are no statistically significant differences between males (mean = 15.840) and females (mean = 16.390) when it comes to behavioral intentions to teach genetics using AI technology. In addition, the associated p-value of 0.282 exceeds the significance threshold of 0.05, so the t-value of -0.581 is not statistically significant. Due to this, the alternative was not supported, indicating that male and female pre-service teachers had similar behavioral intentions when it came to teaching genetics through AI technology.

6. Discussion

Based on the considerable amount of evidence that suggests genetics as a topic in biology is a difficult concept for high school students (Agboghoroma & Oyowvi, 2015; Cimer, 2012; Marbach-Ad et al., 2008; Mueller et al., 2015), it is imperative to explore how to effectively teach the concepts in schools. Realizing the need to adopt new approaches to teaching genetics for better understanding, researchers began to explore different pedagogical techniques. For instance, Onowugbeda (2020) employed an indigenous knowledge strategy while Marbach-Ad et al. (2008) used computer animation and illustration activities to improve high school students’ achievement in molecular genetics among others. However, with the increasing pervasiveness and relevance of AI in the teaching and learning process, adopting AI-based technology to teach becomes essential. To this end, this study explored pre-service teachers’ perspective, attitude, and behavioral intention to infuse AI applications into their instructional during the teaching of genetics in high schools. Furthermore, the effect of gender on each of the variables considered was examined.

The result of SEM analysis revealed that perceived usefulness and subjective norms are antecedents of attitude to use AI while attitude and subjective norms are predictors of behavioral intention to use AI-based applications to teach genetics in a high school education context. However, perceived behavioural control and perceived usefulness could not be linked to the factors that motivate pre-service teachers to adopt AI-based technology. Subjective norms and attitudes found as antecedents of behavioural intention are consistent with past research on technology-related research (Abdel-Maksoud, 2018; Asiri, 2019; Pan et al., 2019; Turan et al., 2022). Contrary to our findings, in the study of Greisel et al. (2023), subjective norms did not predict intentions significantly. This would mean that the factor is dependent on the context, which could be subject/topic related or population. This study found subjective norm as the most significant predictor of behavioural intention to use AI-based systems while for the indirect effect, perceived usefulness is the highest predictor of attitude toward the use of AI. The prominence of a subjective norm is an indication that pre-service teachers’ intention to use AI-based systems is closely tied to how strongly they think that relevant others think they should do so. This could be that the pre-service teachers might believe that they will be admonished by school administrators if they fail to use an AI-based system or using AI to teach could be useful because other teachers or society is gravitating toward the use of AI. This finding has several implications, mainly that policymakers and HEI administrators should encourage the application of AI to the teaching and learning process in teacher education programs. Teacher educators should be empowered through professional development programs to employ AI systems in teaching future teachers. Furthermore, these findings underscore the intricate interplay of perceived usefulness, subjective norms, attitudes, and behavioral intention in shaping pre-service teachers’ adoption of AI-based technology for teaching genetics in high school education. The identified significance of subjective norms suggests a strong influence of social perceptions on pre-service teachers’ intentions, indicating that their decisions are closely linked to perceived expectations from relevant others, such as school administrators or peers. This vital understanding emphasizes the context-dependent nature of subjective norms. The observed prominence of perceived usefulness in predicting attitudes also highlights the pivotal role of utility perceptions in shaping attitudes toward AI adoption.

Against our assumptions, perceived behavioural control did not significantly predict intentions, which is consistent with the findings of Can and Hiğde (2022). The finding is however in contrast with Sungur-Gül & Ateş (2021). Our finding could dictate that pre-service teachers’ intention to utilize AI-based systems is independent of how strongly they think they feel competent, skilled, and equipped with resources to teach genetics using AI technology. Relatedly perceived usefulness could not be positively linked to behavioural intentions to teach with an AI-based platform. This result is consistent with earlier
studies that questioned the relationships between perceived usefulness and behavioural intention (Agudo-Peregrina et al., 2014). Even though sufficient evidence in the literature suggests that perceived usefulness is an antecedent of behavioural intention (Sánchez-Prieto et al., 2017; Sánchez-Prieto et al., 2019), our findings indicate that pre-service teachers believe that using AI technology would enhance their future teaching practices does not guarantee it would be adopted to eventually teach. This would mean that other factors should be considered which include facilitating conditions, relevant knowledge, and pedagogical orientation to implement the application of the emerging technology in the classroom. This finding further suggest that perceived competence, skills, and resources of pre-service teachers may not be decisive factors in determining their intentions to adopt AI technology for teaching. Additionally, the lack of a positive link between perceived usefulness and behavioral intentions challenges established beliefs, suggesting that the conviction among pre-service teachers that AI enhances teaching practices does not necessarily translate into actual adoption. The implication is that factors beyond perceived usefulness, such as facilitating conditions, relevant knowledge, and pedagogical orientation, must be considered to effectively integrate emerging AI technology into classroom teaching.

The result of independent sample t-tests also shows the effect of gender on each of the variables among the pre-service teachers. In the mean difference analysis of pre-service teachers’ gender, a significant difference between males and females was found only in the subjective norm. This shows the importance of other people’s influence in determining how trainee teachers engage in teaching with AI tools. In other words, there is evidence to suggest that the difference between males and females in subjective norm scores is unlikely to have occurred by accident. This supports the alternative hypothesis. There is a higher subjective norm among female pre-service teachers than among male pre-service teachers, based on the results of the study. Regarding AI technology use, females are more likely to be influenced by the opinions of others in their decision-making process. Teachers’ education programs and practices may be affected by the findings. Teachers’ education programs may need to focus on training and support to help female pre-service teachers develop confidence in their decision-making capabilities if they are more likely to be influenced by others’ opinions. Also, the results suggest that gender-specific approaches should be taken when using AI technology in the classroom to teach genetics. Gender has always been a variable of interest in most studies, especially those in science education. The identified gender difference in subjective norm scores among pre-service teachers, specifically with females exhibiting a higher subjective norm than males, highlights the influential role of social factors in shaping attitudes toward AI technology in teaching. This underscores the need for targeted interventions in teacher education programs to address potential gender-based variations in decision-making processes related to technology adoption.

The non-significance of other variables based on gender, is an indication that educators and policymakers shouldn’t assume that perspectives and attitudes toward AI differ significantly by gender. This suggests that both male and female pre-service teachers have similar perceptions of the usefulness of AI technology for teaching genetics, which could inform how AI is introduced and integrated into teacher education programs. It also suggests that gender may not be a significant factor in how pre-service teachers perceive AI use in teaching. In addition, this result suggests that gender may not be important in determining pre-service teachers’ willingness to teach genetics using AI technology. As a result, efforts to create awareness of the utilization of AI technologies in genetics education should not be gender-based. Pre-service teachers, regardless of their gender, should instead be encouraged to use AI technology in teaching genetics to leverage the benefits and advantages that come with using AI technology in the modern teaching and learning environment. In conclusion, it should be noted that the perspectives of teachers considered in this study were limited to a few factors. More factors such as AI knowledge, interest, and motivation, should be considered to understand how pre-service teachers regard the use of AI applications in their future teaching practices. This will further guide the design of interventions aiming to foster pre-service teachers’ engagement with AI-based systems to effectively teach with emerging technologies in their future teaching careers.

To better equip future science teachers to integrate Artificial Intelligence (AI) into their teaching methods, there are essential steps that policymakers in higher education should take. Policymakers are influential in developing pre-service science educators’ ability to incorporate AI into teaching. They must collaborate with AI and education technology experts in creating modules that cover the foundational principles of AI and its applications in science education. Policymakers should also emphasize the
importance of hands-on training with AI tools, ensuring that pre-service science educators have immersive experiences. Providing access to AI resources, software, and simulations empowers educators to integrate AI technologies into their teaching approaches, enhancing their technological proficiency and confidence in using AI to improve student engagement and learning outcomes. Additionally, the long-term integration of AI in science education requires policymakers to allocate resources to research and development initiatives and support studies investigating the impact of AI on teaching and learning outcomes. This evidence-based approach informs future policies and refines teacher education programs to remain relevant in the dynamic landscape of AI integration.

In addition, ongoing professional development is essential for in-service science teachers to stay current with evolving AI technologies and instructional methods. Policymakers should advocate for continuous training and support for in-service educators, fostering collaborations with educational institutions, AI industry leaders, and professional development organizations. Also, customized online and onsite pieces of training focusing on AI integration within science education must be organized for in-service teachers. This proactive approach ensures that transitioning pre-service teachers enter an environment where AI is already integrated when they become in-service. Lastly, policymakers should promote collaborations among educational institutions, the tech industry, and government entities to create a collaborative ecosystem. This facilitates the exchange of ideas, resources, and best practices, elevating the quality of AI integration in science education and establishing a supportive network for pre-service educators as they develop into technologically adept educators.

7. Limitation and future research

We report four limitations that specifically bother the study design. First, we concluded based on the analysis of 90 participants in this study which is relatively small even within the context of the study. Future research should consider a large sample size to increase the generalizability of the findings and generate valuable insight for teaching practices. Second, the study participants only comprise trainee teachers which suggests that they have limited experience or expertise in teaching practices, though they have heard a minimum of three months of practical teaching practice as is customary to teacher teachers in Nigeria. Examining teachers with years of experience teaching genetics will yield invaluable findings for the field. To this end, future work should explore in-service teachers’ perspectives on the use of emerging technology to promote genetics in the classroom. Third, this study could not account for the participants’ preconceptions or existing knowledge about AI use in classrooms though they have been exposed to theoretical knowledge of technology use in education. This seems necessary since teachers’ conception of AI may affect their perspective about its use or relevance for their classroom (Ayanwale et al., 2022) As such, future research may explore teachers’ conceptions of AI to understand the relationship between pre-service teachers’ perceptions of AI and their intention to use it for teaching biology topics. Lastly, this study only utilizes a quantitative approach to analyze the participants’ responses. Future work could adopt a mixed-method approach to triangulate the result and better understand teachers’ views on the use of AI-based applications to teach genetics.

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Appendix 1. Finalized specific items and construct

**Attitude towards AI-tech**

AT1. Teaching genetics in biology classes using Intelligent Tutoring Systems would be useful.
AT2. Teaching genetics in biology classes using Intelligent Tutoring Systems would be comfortable.
AT3. Teaching genetics in biology classes using Intelligent Tutoring Systems would be desirable.
AT4. Teaching genetics in biology classes using Intelligent Tutoring Systems would be purposeful.
AT5. Teaching genetics in biology classes using Intelligent Tutoring Systems would be helpful.
AT6. Teaching genetics in biology classes using Intelligent Tutoring Systems would be effective.
AT7. Teaching genetics in biology classes using Intelligent Tutoring Systems would be beneficial.

**Subjective norm**

SN1. Some of my colleagues have told me not to teach genetics because the course is hard to teach for teachers.
SN2. My colleagues whose opinions I value will encourage me to teach genetics using Intelligent Tutoring Systems.
SN3. My colleagues whose opinions I value will recommend that I teach genetics using Intelligent Tutoring Systems.

**Perceived behavioural control**

PB1. My way of teaching genetics would be clear and understandable using Intelligent Tutoring Systems.
PB3. It would be easier to teach genetics using Intelligent Tutoring Systems if I plan very well before the class.

**Perceived usefulness**

PU1. Teaching genetics using Intelligent Tutoring Systems will increase my effectiveness while in-service.
PU2. Teaching genetics using Intelligent Tutoring Systems will improve my performance while in-service.
PU3. Teaching genetics using Intelligent Tutoring Systems will increase my productivity while in-service.

**Behavioural intention to teach genetics using AI technology**

B1. It is essential to me to teach genetics using Intelligent Tutoring Systems.
B2. I am enthusiastic about teaching genetics using Intelligent Tutoring Systems.
B4. I intend to teach genetics in a scientifically correct way using Intelligent Tutoring Systems.