Computers and Education Open 6 (2024) 100191

Contents lists available at ScienceDirect

Computers and Education Open

journal homepage: www.sciencedirect.com/journal/computers-and-education-open

Do in-service teachers accept artificial intelligence-driven technology? The mediating role of school support and resources

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ARTICLE INFO

Keywords:
Artificial intelligence in education
In-service teachers
Lesotho education
School support for technology
Teacher attitudes towards AI
Unified theory of acceptance and use of technology

ABSTRACT

This study investigates the acceptance and utilization of artificial intelligence (AI) among in-service teachers in Lesotho, focusing on the mediating role of school support and resources (SSR). In Lesotho's educational landscape, which is characterized by a growing interest in technology integration, this study fills an essential gap in the existing literature by exploring in-service teachers' perspectives on AI adoption and the mediating influence of SSR. Using the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical framework, the study adopts a cross-sectional design, collecting data from a sample of 315 in-service teachers through online surveys. The data was analyzed using maximum likelihood estimation. The results reveal a substantial positive relationship between perceived usefulness, perceived ease of use, and a positive attitude towards AI, with SSR playing a pivotal role as a complementary mediator in these connections. However, the study identifies a non-significant relationship between technical proficiency and behavioral intention, suggesting a need for further investigation into the technical skills essential for effective AI integration. The results highlight the critical role of SSR in shaping in-service teachers' intentions to use AI in their teaching practices. As a result, the study recommends tailored continuous professional development programs and collaborative learning communities to enhance teachers' skills. Additionally, it emphasizes the importance of advocating for policies that support AI integration in education and underscores the ethical considerations related to AI use. We discuss the implications of our results concerning integrating AI into teachers' teaching practices in schools and outline future directions.

1. Introduction

Today, the world is undergoing a significant technological disruption marked by breakthroughs such as cybersecurity, robotics, machine learning, the Internet of Things (IoT), deep learning, and artificial intelligence (AI) [1,2]. These technological innovations, especially AI, have had a widespread impact across various sectors, including education. To better understand the concept of AI, it is crucial to define it. The definition of AI appears to be multifaceted, but researchers widely acknowledge AI as a set of sciences, theories, and techniques concerned with the development of intelligent machines that can learn, adapt, synthesize, and self-correct like humans [3–5]. In response to the influence of AI, Ali [6] highlighted that the education sector is actively embracing the opportunities and challenges brought about by technology, with a particular focus on enhancing teaching and learning through AI. This transformation is part of what Ayanwale [1] describes as the fourth industrial revolution (IR 4.0) in education. Similarly, Ahmad et al. [7] perceive AI as the new electricity of this era, which countries such as China and America invest in for their developmental growth in different sectors, including education. Further, one area of AI that is beginning to gain attention is generative AI. According to Feuerriege et al. [8], generative AI, particularly models such as ChatGPT, is gaining prominence for its transformational potential in education. Generative AI is a subclass of AI technologies which concentrates on producing new material, such as images, words, or music, using patterns learned from large datasets [9]. This technology has the potential to generate educational resources, personalize learning experiences [10]. As we learn more about AI, it becomes apparent that generative AI will certainly have a significant part in creating the future of education.

To understand the acceptance and use of AI towards in-service

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https://doi.org/10.1016/j.caeo.2024.100191
Received 30 January 2024; Received in revised form 2 May 2024; Accepted 20 May 2024
Available online 21 May 2024

teachers, it is crucial also to understand the challenges and opportunities presented by AI in the context of education. Regarding benefits, Zhang et al. [11] highlight that AI enhances the quality of teaching and learning processes, opening up new opportunities for both educators and students. One of the opportunities, as noted by Shirin [12], is that AI may be used by teachers to help create learning activities and scaffolding tactics. Additionally, it assists in easing the analysis and display of student information, as well as providing indications for a variety of learning-related outcomes, including achievement and cognitive state. However, while many people recognize the potential benefits of AI in education, there are also concerns. One of the concerns noted by Gocen and Aydemir [4] is that some teachers are reluctant to adopt AI-enhanced technology due to fear that it might replace teachers and lead to job loss. The mixed opinions based on AI in education are evidence that AI receives increasingly nuanced perceptions. Existing studies on AI include a study in Korea by Seo et al. [13], which found that teachers envision that adopting AI systems in online learning can enable personalized learner–instructor interaction. Another study in Germany by Zhang et al. [11] found that perceived ease of use and perceived usefulness were identified as primary factors predicting pre-service teachers' intention to use AI. Furthermore, a study in Nigeria by Ayanwale and Sanusi [14] found that teacher perceptions of AI for social good and confidence did not have a moderating effect on the relationship between teachers' readiness to adopt AI education and behavioral intention. In the context of Lesotho, a study by Ayanwale [1] though not using in-service teachers found that students in Lesotho held a positive attitude toward learning AI. Ayanwale and Molefi [15] also conducted a study which revealed a noteworthy correlation between the perceived relative advantages of chatbots and the behavioral intention of students to utilize them. This indicates that students showcase an understanding of the advantages linked to utilizing AI tools and display a willingness to incorporate them into their academic pursuits.

There is limited research addressing the in-service teachers' acceptance and use of AI and the influence of schools' support and resources. Previous studies primarily focused on AI in education outside Lesotho ([13]; Sanusi & [1,11]), thus failing to provide insight into the acceptance and use of AI by in-service teachers in the context of Lesotho. While there have been some studies conducted in Lesotho about technology integration in education and AI [1,16–19], however, they did not focus on the use and acceptance of AI among in-service teachers and the mediating influence of school support and resource availability in effectively integrating AI technology. Numerous studies have only looked at the relationship between variables such as perceived ease of use (EU), perceived usefulness (PU), attitude (AT), technical proficiency (TP) and behavioural intention (BI) [1,20–23]. There is a dearth of research on the role of school support and resources (SSR) as a crucial mediating variable between AT, EU, PU, TP and BI. Therefore, the current study is unique since it examines in-service teachers' willingness and ability to adopt AI technology in their teaching practices, emphasizing the importance of the mediating variable of school support and resource availability within Lesotho's educational system.

Our study aims to contribute to the existing literature on AT, EU, PU, TP, and BI by examining how school support and resources mediate the adoption and utilization of AI in teaching contexts by in-service teachers. While previous research has primarily focused on individual-level factors, our study seeks to highlight the crucial role of school support structures and resources in promoting the integration of AI within educational settings. By addressing this gap in the literature, our study does not only advance theoretical understanding of technology adoption but also provides practical insights for educational policymakers, school administrators, and teacher professional development programs that wish to harness the potential of AI to enhance teaching and learning outcomes. Additionally, this study contributes to our understanding of AI acceptability and use among in-service teachers in Lesotho through investigation into the moderating influence of school support and resources. By focusing on the Lesotho context, this study provides understanding into the unique problems and opportunities associated with AI integration in education in this environment. The study will provide a comprehensive review of literature on the acceptance and use of AI in education, AI in sub-Saharan countries, and critiques and challenges of AI-driven technology. Furthermore, the study described the research design, data collection methods, sample selection, and data analysis techniques used in the study. The study also looked into data presentation, discussion of the findings, conclusions, and recommendations.

2. Literature review

2.1. AI in education and its importance

Artificial Intelligence has become an integral part of various industries, influencing various aspects of our lives. Today, its potential for revolutionizing education is gaining much recognition, even in the education sector. This has been affirmed by Oyelere et al. [24], who note that incorporating AI into the education sector is gaining recognition as a means to align with the contemporary need for technology-driven education. Researchers commonly agree that AI is revolutionizing and depicting a new era of education that is inclusive and compatible with the diverse requirements of individual learners [4,25]. The issue of inclusivity, which AI seems to address, is crucial. As explained by UNESCO [26], AI technologies, such as intelligent tutoring systems and chatbots, provide accessible learning opportunities for marginalized people and those living in isolated communities. This inclusivity of AI is also affirmed by Miao et al. [27], indicating that the integration of AI promotes inclusion, equity, and gender equality. Integrating AI into education is crucial in the 21st century, considering that education demands the use of AI. One advantage of AI in education, as highlighted by Bajaj and Sharma [28], is that AI can help teachers improve personalized instruction for learners. In other words, AI can assist educators in creating a more customized and effective learning experience for each student, taking into account their strengths, weaknesses, and unique preferences. This view is affirmed by Sekeroglu et al. [29], who concur that personalized learning provides students with an opportunity to learn at their own pace and in a manner that suits an individual's learning style. Haseski [30] and Shirin [12] further note that AI assists teachers in evaluating data related to students' learning outcomes, such as cognitive state and achievement. This information can be crucial for teachers to identify areas where students may need extra support, adapt their teaching strategies, and ensure that each learner is making progress in their education. The highlighted usefulness of AI here shows how crucial school support could be to influence the use and acceptance of AI by teachers in their teaching practices.

2.2. Use of AI in education

The adoption and acceptance of AI in education signifies a paradigm shift in the way teaching and learning are approached. The UNESCO [26] is clear that AI in education should be for the common good. It encourages countries around the globe including Africa to strive for the integration of AI in education. As stated by Karaca and Kilcan [31], the adoption of AI in Education has witnessed rapid growth, propelled by its potential to revolutionize traditional teaching methods to technology-driven teaching. Without a doubt, the world seems convinced that the integration of AI in education acts as an intelligent teacher since it improves the quality of teaching learning and assessment. Kamalov et al. [32] bear witness to this view, noting that 40 % of time spent by teachers on grading and other related activities is now efficiently spent by a teacher in the provision of more learning support to students. It is based on this perceived usefulness that one would concur with UNESCO [26] and urge that stakeholders in education accelerate their initiatives towards integrating AI into education to avoid falling back in this rapidly changing world.

2.3. Teachers' intentions to use AI

Artificial intelligence (AI) plays an essential role in stimulating innovation and driving transformation across multiple industries, because of its ability to handle large datasets, recognize patterns, and make autonomous judgements [11]. Education stands out as a subject where AI has immense potential, particularly in delivering individualized learning experiences adapted to the specific needs of individual students [26]. However, in-service teachers' readiness and willingness to incorporate AI technology into their teaching methods is a crucial factor in the effectiveness of these breakthroughs in education contexts [33]. According to Fokides' [34] study, behavioral intention is a significant measure of the factors that influence desired behavior, such as the use of AI by in-service teachers. Individuals' behavioral intention, which is influenced by their ideas and perceptions, defines the amount of effort they are willing to put in when performing a specific behavior.

Various theories attempt to explain people's intentions to adopt breakthroughs such as AI. According to Rogers' Innovation Diffusion Theory (1995), various influential components exist, the most influential of which is perceived benefit or performance expectancy, as highlighted by An et al. [20]. This element in the context of the study, indicates people's willingness to adopt AI-powered solutions if they believe they will provide real benefits such as improved teaching effectiveness and student learning outcomes. Furthermore, compatibility is important, as in-service teachers are more inclined to adopt AI if they believe it is consistent with their teaching philosophies and pedagogical practices. Complexity, which in the setting of the study represents the perceived difficulty of adopting and integrating AI technology, influences teachers' behavioral intentions to use AI. According to Fokides [34] and Druga et al. [35], their studies revealed that school resources and support play an important role in facilitating the effective integration of AI-driven technologies into classrooms.

Schools empower teachers to successfully use AI-driven technology in their teaching practices by providing essential training, professional development opportunities, technical assistance, and access to the necessary infrastructure and tools. This support system ensures that teachers have the essential skills and knowledge to effectively utilize AI, which improves teaching and learning results are revealed in studies of Ayanwale et al. [36] and Bojorquez and Vega [37]. Schools, for example, can organize workshops and seminars on AI literacy, AI teaching knowledge, and AI teaching practice knowledge, allowing teachers to develop the competences required to easily integrate AI into their teaching techniques. Such programs not only provide teachers with the necessary technical skills, but also develop a better awareness of how AI may improve methods of teaching, student engagement, and achievement. Furthermore, school support and resources are vital in addressing the many obstacles and concerns associated with AI adoption in education, such as data protection, equity, and ethical use [38]. Schools can ensure that AI technologies are utilized responsibly and ethically by giving teachers with the materials and support they need, protecting against any biases and discriminatory practices. This proactive approach not only creates an ethical AI culture, but it also develops an inclusive learning environment in which all students may benefit from the opportunities provided by AI-powered technology [39].

Understanding in-service teachers' behavioral intentions to use AI is becoming increasingly important in education, since AI provides innovative opportunities for improving teaching techniques. For example, An et al. [20] discovered that English as a foreign language (EFL) teachers have good attitudes towards AI and high ambitions to implement technology into teaching. Facilitating conditions, such as the usefulness and accessibility of use of AI technology, as well as supportive attitudes from schools and colleagues, have been positively associated with teachers' behavioral intention to adopt AI. Sanusi et al. [40] also emphasized the importance of providing professional development to in-service teachers for them to use AI effectively. According to the data from the study, teachers' confidence in teaching AI predicts their intention to teach it, but AI relevance has a big influence on preparedness for using AI in classrooms. However, anxiety and beliefs about social good had no meaningful impact on teachers' willingness or readiness to use AI technology. Understanding these aspects is important for developing effective support systems to ease the integration of AI into education. Understanding teachers' behavioral intentions towards AI usage in Lesotho is critical for the successful integration of artificial intelligence into classroom activities.

2.4. AI education in Sub-Saharan countries

The integration of AI in Sub-Saharan countries has become a subject of interest, reflecting the global trend of technological advancements. According to UNESCO [26], Africa can benefit from AI education, considering it has a higher proportion of young people than any other continent [41]. The potential benefit lies in the fact that this youthful population could transfer AI competencies for the socioeconomic development of Sub-Saharan countries. There are promising initiatives in Sub-Saharan countries regarding AI integration. UNESCO [26] highlights projects like M-Shule in Kenya, which uses AI-powered SMS messages to provide education, even in areas with limited internet access. Additionally, in South Africa, the Ms Zora platform serves as a coding and robotics software tool to assist teachers and act as learners' tutors [42]. In the context of Lesotho, Ayanwale [1] noted that a considerable number of students showed a positive attitude towards learning AI. These instances validate the idea that Sub-Saharan countries still have the opportunity to leapfrog towards the effective implementation of AI. However, we cannot overlook the challenges facing Sub-Saharan countries in the adoption of AI in education. UNESCO [26] indicates that Africa is falling behind in the integration of AI in education, with an overt indicator being that, despite member states implementing AI curricula, none are from Africa. Oyelere et al. [41] express the view that AI applications are usually developed abroad, lacking African context and posing challenges for easy usage and adoption. Gwagwa et al. [42] highlight that Africa's ranking on the global Government Artificial Intelligence Readiness Index is very low. Furthermore, UNESCO [43] notes that one challenge of the integration of AI in education is the shortage of skilled teachers to manipulate technology and inadequate resources provided by schools. This evidence suggests that even though there are initiatives to integrate AI in Africa, effective implementation is still challenged. Therefore, infrastructure, internet access, and gadgets are essential [19,21]. The acceptance and utilization of AI tools by in-service teachers can be influenced by their availability, as well as their cultural and linguistic suitability for the African environment [41]. Additionally, there are ongoing efforts in Africa to incorporate AI, which are worth noting.

2.5. Critiques and challenges of AI-driven technology

Even though AI-driven technology has some benefits, there are also challenges associated with it. UNESCO [26] highlighted digital connectivity as one of the challenges associated with AI. Despite the potential benefits AI could bring to communities, it is acknowledged that there are disparities in digital connectivity, particularly in developing countries such as Lesotho. Another challenge of AI integration is its limitation in meeting the highest ethical considerations. The Support from Ntoutsi et al. [44] explained that if AI is not properly designed and trained, it could perpetuate societal biases potentially leading to discriminatory outcomes. This situation often occurs since huge AI models such as ChatGPT are trained on a larger amount of data containing different views. In such cases, the likelihood of biases is inevitable and could negatively impact students' learning outcomes. Moreover, privacy is one of the central concerns associated with AI-driven technology. Miao et al. [27] express concerns about the large amount of data which is collected and being processed by AI systems. The debate often centers on the vulnerability of personal data and communications, which is susceptible to hacking. The concern in the present case is a need for robust privacy regulations through the implementation of policies that safeguard individual privacy. Furthermore, plagiarism is one of the critiques levelled against. Chen et al. [45] indicate that plagiarism has become a significant concern since the introduction of AI-driven technology. The worry is that if the prevalence of AI persists as such, it is clear that academic integrity is under threat. Therefore, there is a need for policies regulating academic misconduct using AI.

2.6. Theoretical framework and hypotheses development

The study adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) since it aims to explain user intentions to use an information system while taking into consideration social factors [46]. The UTAUT is a comprehensive framework that extends and integrates various theories to explain the acceptance and use of technology. This framework extends the two main variables of the technology acceptance model (TAM), namely, perceived usefulness (PU) which is the extent to which a user believes using technology brings certain advantages [21] and perceived ease of use (EU) that is referred to as the degree in which using a certain technology is effortless [23]. In addition, the theory also acknowledges the importance of constructs such as attitude (AT), and behavioural intention (BI). AT pertains to users' positive or negative feelings about using technology [47] while BI refers to the users' intention or willingness to use technology [48] which is influenced by PU, EU, and AT. The other four key core constructs which include the following: first, the performance expectancy, which investigates their perceptions of the performance benefits of incorporating AI-driven technology in their teaching practices. Second, is the effort expectancy which examines the in-service teachers' perceptions of the ease of use of AI-driven technology. Third, the social influence explores the influence of stakeholders on teachers' decisions to adopt AI-driven technology. Lastly, the facilitating conditions focus on the extent to which institutional support and resources facilitate the use of AI-driven technology among in-service teachers [49–51]. As a result, the research specifically investigated the interaction among the following constructs: perceived usefulness, perceived ease of use, attitude, technical proficiency, and teachers' behavioral intention to use AI-driven technology in their teaching practice. These factors were influenced by a mediating variable, namely facilitating conditions, with a specific focus on school support and resources, as illustrated in Fig. 1.

2.6.1. Perceived Usefulness (PU)

The concept of perceived usefulness pertains to the extent to which teachers believe that technology especially AI will assist them in achieving their instructional objectives [21,47,52] while behavioral intention refers to the probability that teachers will integrate technology into their teaching practices [21,53]. Previous studies have only explored the relationship between perceived usefulness and intention to use technology ([21,23]; Sing [11,48]). However, there is limited research on the role of school support and resources as mediating variable between PU and the intention to use AI. The provision of school support and resources encompasses the assistance and resources offered by educational institutions to aid teachers in utilizing AI, such as access to technology, financial backing, and professional development opportunities [54]. This suggests that for teachers to adopt AI, schools need to provide assistance resources so that teachers can genuinely believe in AI's utility. Nonetheless, this belief in isolation does not guarantee the adoption of AI by teachers, as there are various factors such as the provision of school support and resources that significantly influence their acceptance and utilization of AI in their instructional methods [54]. For instance, if a teacher is granted access to an AI technology-based teaching tool without receiving any training or support from the school on how to employ it, the likelihood of the teacher utilizing the tool is low, even if they perceive it to be beneficial. Conversely, if the teacher is provided with training and support from the school, they are more inclined to make use of the tool, even if they harbor doubts regarding its usefulness. This phenomenon can be attributed to the support and resources furnished by the school, which subsequently bolsters the teachers' confidence and proficiency in utilizing AI-driven technologies in the classroom. It is important to note

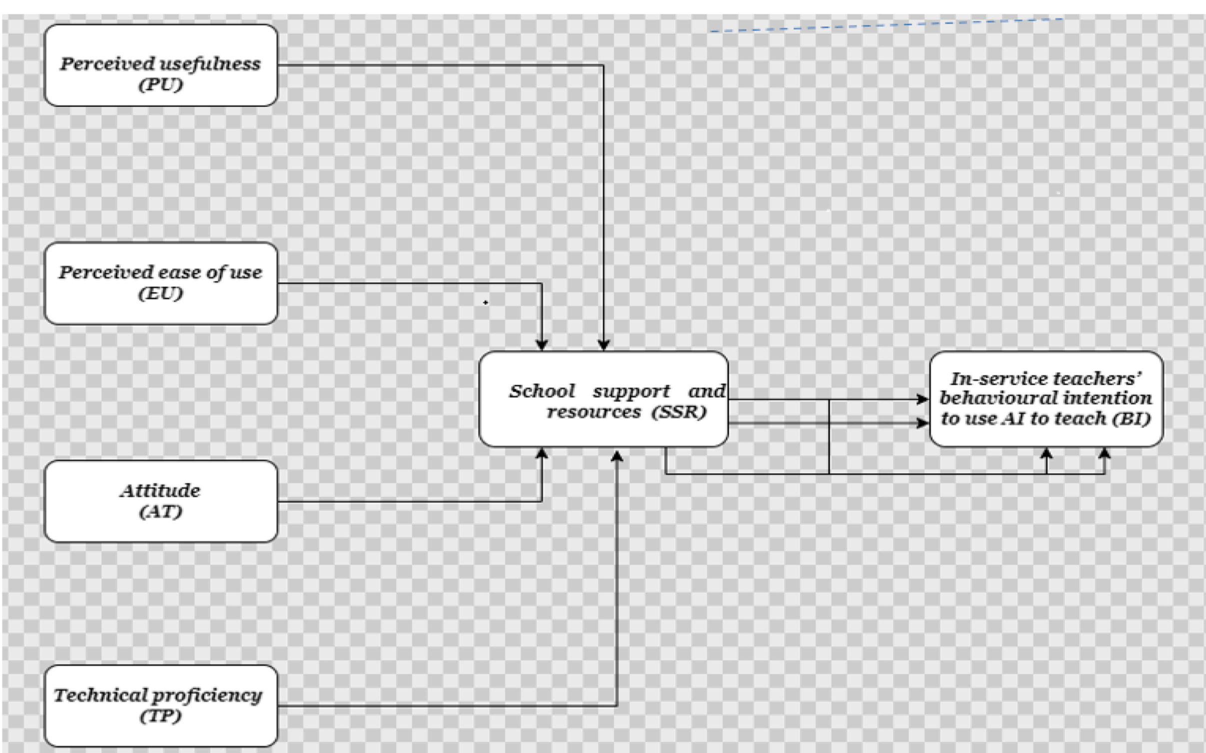

Fig. 1. Research conceptual framework.

that perceived usefulness by itself does not serve as a predictor of whether or not teachers will integrate AI into their teaching practices; rather, the mediating variable of school support and resources plays a significant role. Hence, we therefore hypothesize:

H1. *The impact of perceived usefulness on in-service teachers' behavioral intention to use AI to teach is significantly influenced by the mediating variable of school support and resources.*

2.6.2. Perceived ease of use (EU)

Perceived ease of use refers to the extent to which an educator holds the belief that utilizing a specific technological tool or technology will be effortless and devoid of exertion [47]. In essence, it is the degree to which the teacher is convinced that employing the tool will be uncomplicated, direct, and not excessively time-consuming [23,55]. It is crucial to comprehend that the EU diverges from the actual ease of use. A tool may possess EU qualities, yet in practice, it could prove to be rather intricate and arduous to operate. EU is a subjective norm [1], whereas actual ease of use is an objective norm. EU stands as a significant determinant in forecasting a teacher's inclination to employ AI in their pedagogy. For instance, a study conducted by Zhang et al [11] portrays that if a teacher deems AI usage to be simple and effortless, they are more inclined to genuinely utilize it in their teaching. Further, the results show that EU and PU are crucial factors that influence pre-service teachers to adopt and use AI in their classes. Another study by Al-Darayseh [56] demonstrates that the teachers' perception of EU of AI applications contributes to their positive attitudes and behavioral intentions towards the future adoption of AI. This outcome is in line with the findings of Lillian-Yee-Kiaw et al [57]. The results are also consistent with the study conducted by Wang et al. [58], which indicates that teachers' EU has a positive impact on their attitudes towards the adoption of AI applications, thereby leading to an increased acceptance of these applications in science education. Moreover, it is noteworthy to acknowledge that this correlation is mediated by the support and resources provided by the school. In other words, despite perceiving AI as an easy-to-employ tool, a teacher's intention to utilize it in this study may be influenced by other factors such as the availability of resources [54]. It is apparent that if the school furnishes suitable training, guidance, and support, the teacher is more prone to feel self-assured in harnessing AI and consequently more inclined to use it. Conversely, if the school fails to provide adequate support, the teacher may feel overwhelmed and less likely to employ AI, even when perceiving it as easy. As a result, we hypothesize:

H2. *The impact of perceived ease of use on in-service teachers' behavioral intention to use AI to teach is significantly influenced by the mediating variable of school support and resources.*

2.6.3. Attitude towards AI-driven (AT)

Attitude refers to the general positive or negative sentiment that a teacher possesses regarding the utilization of AI in their teaching practices [1,21,47]. Like the EU, AT is a subjective factor that can influence the intention to use AI. The relationship between ATT and the intention to use AI in this study is mediated by the schools' support and resources. Rahiman and Kodikal [54] highlight that the connection between ATT and the intention to utilize AI is mediated by the support and resources provided by the school support and resources. Consequently, even if a teacher exhibits a favorable attitude towards utilizing AI, their intention to employ it may be impeded by the level of assistance they receive from the school [59]. For instance, a study conducted by van Twillert et al [60] emphasized the adequacy of the school's technological infrastructure as a pivotal consideration. This suggests that the instructor's utilization of AI becomes more likely if the school possess contemporary technological infrastructure. Furthermore, the presence of an information technology (IT) department within the school that can offer guidance on technical matters instills a greater sense of confidence in instructors when employing AI [54]. Lastly, the opportunities for professional growth available within the school can also play a significant role. It is apparent that if the school provides training and support to facilitate instructors' acquisition of knowledge and proficiency in AI, the instructors' level of confidence in their ability to utilize the AI technology becomes a crucial factor. When instructors feel assured and capable of utilizing AI, their propensity to cultivate a positive attitude and intention to employ AI increases [54]. This implies that instructors who maintain the conviction that AI can enhance their instructional practices and benefit students are more likely to adopt a positive attitude and intention towards its utilization. Moreover, instructors' perceptions of the social and cultural implications associated with AI assume a pivotal role. Specifically, if instructors perceive that the use of AI is socially acceptable and culturally appropriate, they are more inclined to harbor a favorable attitude towards AI and elevate their intention to employ it. Therefore, we posit the following hypothesize:

H3. *The impact of attitude on in-service teachers' behavioral intention to use AI to teach is significantly influenced by the mediating variable of school support and resources.*

2.6.4. Technical Proficiency (TP)

Technical proficiency can be explained as the proficiency and knowledge needed to utilize AI technology with efficacy [61]. This encompasses comprehending how to operate specific technologies, as well as possessing the ability to troubleshoot and resolve issues as they arise. TP can be cultivated through training, experience, and practical application. Within the realm of AI, it can also encompass comprehending the ethical, legal, and privacy implications of employing AI within the educational setting [21,62,40]. Moreover, it can also entail gaining an understanding of how to utilize AI in instructional methodologies, and how to effectively employ AI-powered platforms and tools while also having the ability to adapt and customize them to meet the specific needs of the classroom [21,63]. It can be argued that the support and resources provided by the educational institution play a significant role in influencing TP. If the school offers sufficient training and support, the teacher will likely develop the TP necessary to effectively employ AI. This will have an impact on the teacher's intention to utilize AI, resulting in positive outcomes for both the teacher and the students. The infrastructure and technical support provided by the school are crucial factors that can influence TP. If the institution possesses outdated equipment or insufficient support, the teacher's TP is likely to be diminished. We therefore proposed the hypothesis below:

H4. *The* impact *of technical proficiency on in-service teachers' behavioral intention to use AI to teach is significantly influenced by the mediating variable of school support and resources.*

3. Methodology

3.1. Procedure, research context and participants

Responding to the widespread technological disruptions across various sectors, including education, the Ministry of Education and Training in Lesotho recognized the need to equip their teachers with the essential skills to navigate this changing landscape. As a result, the training sessions aimed to provide in-service teachers with comprehensive knowledge and practical skills for integrating AI-driven technology into their teaching practices. These sessions combined presentation-based learning and interactive discussions to cater for different learning styles and promote active engagement among participants. The training format allowed participants to receive information, discuss, and share experiences, fostering a collaborative learning environment. This approach aligns with best practices for professional development, emphasizing the effectiveness of interactive and participatory training methods. Each training session varied in duration, typically 4 to 5 h, depending on the content and activities covered. The training program spanned three weeks to give participants enough time to absorb information, practice new skills, and reflect on their learning. The content of the training sessions was tailored to meet the needs and interests of in-service teachers. It focused on practical applications and real-world examples of AI-driven technology in educational settings. Topics covered included an overview of AI technology and its potential impact on teaching and learning, hands-on exercises demonstrating AI tools and platforms, and discussions on ethical considerations and best practices for integrating AI into pedagogical methods. Participants were also provided resources and materials to support their continued learning and exploration of AI technology beyond the training sessions.

This research was conducted within public secondary schools, recognizing the importance for Lesotho to actively engage in the ongoing global technological revolution, particularly in the realm of AI literacy that significantly influences various aspects of our daily lives. The study aimed to capture the insights of in-service teachers who had undergone initial professional development training in integrating AI-driven technology into their teaching practices. Additionally, it sought to explore the impact of school support resources on shaping their intentions to use AI technology, along with other factors.

The demographic data presented in Table 1 provides insights into the characteristics of respondents in terms of gender, age group, school location, teaching experience, area of teaching, level of technology usage, and training on integrating AI technology into teaching. When it comes to gender distribution, the majority of respondents are female, accounting for 56.2 %, while males make up 43.8 %. Looking at age groups, the largest proportion falls within the 25–34 years category, making up 44.1 %, closely followed by the 35–44 years group at 42.2 %. Younger respondents may have a higher level of technological familiarity, which could facilitate the integration of AI-driven tools. In terms of school location, 60.0 % of respondents are from urban areas, while 40.0 % are from rural areas. The difference between urban and rural areas may affect the availability and accessibility of technology infrastructure. In terms of teaching experience, the distribution is relatively balanced across categories. This diversity in teaching experience levels highlights the need to design training programs that cater to novice and experienced teachers, ensuring the effective integration of AI-driven technology into their teaching practices. Analyzing the area of teaching, Science, Technology, and Mathematics, emerge as the predominant subjects, making up 50.5 % of respondents, followed by Linguistic and Literary subjects at 34.0 %. Customizing AI applications to align with these subjects has the potential to enhance teaching methods and the delivery of content in these domains. In terms of the level of technology usage, the majority of respondents have a Basic level of proficiency at 53.7 %, followed by Intermediate at 34.9 %.

Table 1
Demographic information of the respondents.

Variable	Characteristics	Frequency	Per cent
Gender	Male	138	43.8
	Female	177	56.2
Age group	Below 25 years	13	4.1
	25-34 years	139	44.1
	35-44 years	133	42.2
	45-54 years	18	5.7
	55 and above years	12	3.8
School location	Urban	189	60.0
	Rural	126	40.0
Teaching experience	1- 5 years	115	36.5
	6- 10 years	98	31.1
	11- 15 years	51	16.2
	16 and above years	51	16.2
Area of teaching	Science and Technology and Mathematics	159	50.5
	Personal, spiritual and social	27	8.6
	Linguistic and Literary	107	34.0
	Creativity and Entrepreneurship	22	7.0
Level of technology usage	None	18	5.7
	Basic	169	53.7
	Intermediate	110	34.9
	Advance	18	5.7
Training on AI technology integration into teaching	Yes	315	100

3.2. Measures

In this study, the survey included six sets of scales covering various aspects: perceived usefulness of AI-driven technology, perceived ease of use, technical proficiency, school support and resources, attitude towards AI-driven technology, and behavioral intention to use AI-driven technology. In-service teachers were asked to rate their level of agreement with each item on a scale of 1–6, where 1 = "strongly disagree" and 6 = "strongly agree." The questionnaire was written in clear and straightforward English to prevent any potential ambiguity. As shown in Table 2, the assessment of the perceived usefulness of AI-driven technology drew from established and validated studies, specifically utilizing the five-item scale by Ayanwale et al. [21] and Zhang et al. [11] (Cronbach alpha reliability = 0.837). Similarly, the evaluation of the perceived ease of use of AI-driven technology was based on existing literature, using the five-item scale by Zhang et al. [11] (Cronbach alpha reliability = 0.871).

Technical proficiency was measured using the five-item scale by Zhao et al. [61] (Cronbach alpha reliability = 0.866). The measurement of school support and resources used the five-item scale by Rahiman and Kodikal [54] (Cronbach alpha reliability = 0.856). The assessment of attitude towards AI-driven technology relied on a three-item scale by Ayanwale et al. [21] (Cronbach alpha reliability = 0.819), and the behavioral intention to use AI-driven technology for teaching practices were evaluated with the four-item scale by Ayanwale et al. [21] (Cronbach alpha reliability = 0.813). Minor adjustments were made to the wording of items from all six scales to ensure their appropriateness within the context of the current study.

3.3. Data collection procedures and ethical consideration

Data were collected from in-service teachers in government-owned schools. Before data collection, the study followed the ethical principles outlined in the Declaration of Helsinki, an internationally recognized set of ethical guidelines for research involving human subjects [64]. The teachers were provided with detailed information about the study's purpose, participation, and potential risks or benefits. They were free to decide whether or not to participate, and their consent was obtained before proceeding with the study. Personal information and responses were treated with the highest level of confidentiality, and the data was anonymized to ensure the identities of the teachers remained protected. Additionally, there was a significant time gap of approximately six to seven months between the training and the survey administration. This deliberate waiting period allowed the teachers ample time to reflect on their experiences and apply the newly acquired knowledge and skills in their teaching practices. Furthermore, the study was thoroughly reviewed by the relevant ethics committee associated with the researcher's institution. The survey link for the study (https://forms.gle/RgPha2a2thKajG2g8) was shared with teachers through various channels, including teachers' association platforms and WhatsApp, to encourage broad participation and engagement. A large audience of teachers was reached by taking advantage of these established networks. Teachers' associations often serve as central hubs for communication and collaboration among teachers. Additionally, the survey was shared through WhatsApp, leveraging its popularity and accessibility. WhatsApp groups, often created by teachers for professional collaboration, provided a convenient space for disseminating information about the study. The Google form questionnaire took approximately 10 to 15 min to complete and was open for data

Table 2
Source of construct and items.

Construct	Source	Items
Perceived Usefulness of AI-driven technology	Ayanwale et al. [21], and Zhang et al. [11]	PU1- I believe incorporating AI technology into teaching practices would improve students' understanding of complex concepts. PU2- Using AI-driven tools would increase students' engagement and participation in classroom activities. PU3-Using AI technology can help personalize learning experiences for students with different learning styles and abilities. PU4-Integrating AI into teaching would make the learning process more interactive and dynamic for students. PU5-AI-driven technology is useful in providing instant feedback to students, aiding their learning progress
Perceived Ease of Use of AI-driven technology	Zhang et al. [11]	EU1-I can quickly learn and adapt to new AI tools introduced in a teaching environment. EU2-I find it easy to deal with challenges related to AI tools usage during teaching sessions EU3-I find AI-based systems to be user-friendly EU4-Operating an AI-based system does not require a lot of mental effort EU5-The operation of an AI-based system is clear and understandable
Technical Proficiency in AI-driven technology	Zhao et al. [61]	TP1-I engage in self-directed learning to improve my technical skills, including the use of AI applications TP2-I feel confident in troubleshooting technical issues related to AI tools without external assistance TP3-I can explore and experiment with various AI applications to enhance my teaching methods TP4-I collaborate with colleagues or attend workshops to improve my technical proficiency in using AI-driven technology for teaching TP5-I agree that continuous improvement of technical skills is essential for effective integration of AI technology into teaching
School Support and Resources for AI-driven technology	Rahiman and Kodikal [54]	SSR1-Our school provides adequate AI-driven tools and resources for teaching SSR2-I have access to the necessary AI teaching tools and materials SSR3-Resource availability positively affects my readiness to teach using AI-driven tools. SSR4-The school's investment in AI resources supports my AI teaching efforts SSR5-There are dedicated personnel in my school to assist with AI implementation in teaching
Attitude towards AI-driven technology	Ayanwale et al. [21]	AT1-Using AI technology is pleasant AT2-I find using AI technology to be enjoyable AT3-I have fun using AI technology
Behavioural intention to use AI-driven technology	Ayanwale et al. [21]	BI1-I intend to use AI-driven technology in my teaching practices. BI2-I plan to actively seek opportunities to learn and use AI tools in my teaching. BI3-I intend to use and experiment with different AI applications for educational purposes. BI4-I intend to consistently use AI technology in various aspects of my teaching activities.

collection for three months (October to December 2023) before it was closed.

3.4. Method of data analysis

We used covariance-based structural equation modeling (CB-SEM) with the Analysis of Moment Structure (AMOS) software version 26.0 [65]. The primary aim was to investigate the mediating role of school support and resources in the relationships among the constructs. Memon et al. [66] caution researchers against solely relying on statistical programs like AMOS; instead, they emphasize the importance of justifying the chosen sample size. To assess sample size adequacy, we followed an a-priori sample size determination for structural equation models, as suggested by Soper [67]. This involved employing an online power analysis application accessible at https://www.danielsoper.com/statcalc/calculator.aspx?id=89. The application considered inputs such as the number of observed variables (27 items measuring the constructs) and latent variables (six variables in total), the expected effect size (0.25 for a medium effect), the anticipated probability (95 % significance level), and the statistical power level (80 %). The online power analysis application determined the minimum sample size required for detecting the specified effect based on the structural complexity of the model (see Fig. 2). Various studies, including Valaei and Jiroudi [68], Balaji and Roy [69], Dedeoglu et al. [70], Yadav et al. [71], and Kuvaas et al. [72] have endorsed this approach for determining a study-specific minimum sample size considering the number of latent and observed variables. This method is recognized as superior to other online sample size calculators. The sample size used in this study aligns with the recommended size, signifying sufficiency. Notably, 444 responses were initially collected post-online survey administration, but the analysis considered 315 responses. Excluded were 129 in-service teachers who reported no participation in the AI training organized by the Ministry of Education and Training.

Moreover, we conducted Confirmatory Factor Analysis (CFA), and mediation analysis and assessed the reliability of our survey instrument by calculating Cronbach's alpha and Composite reliability for each construct. Convergent validity was evaluated based on each construct's Average Variance Extracted (AVE). Before conducting the CFA, we examined assumptions such as sample size adequacy, normality, multicollinearity, linearity, and any outliers in the dataset. The CFA employed the Maximum Likelihood Estimation method, which was chosen to meet the normality requirements of our estimation approach. Next, we used various statistical measures to evaluate how well the model fits the data. These measures included the Relative Chi-Square Test, Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Tucker Lewis Index (TLI), Comparative Fit Index (CFI), Normed Fit Index (NFI), Adjusted Goodness of Fit Index (AGFI), and Goodness of Fit Index (GFI). We interpreted

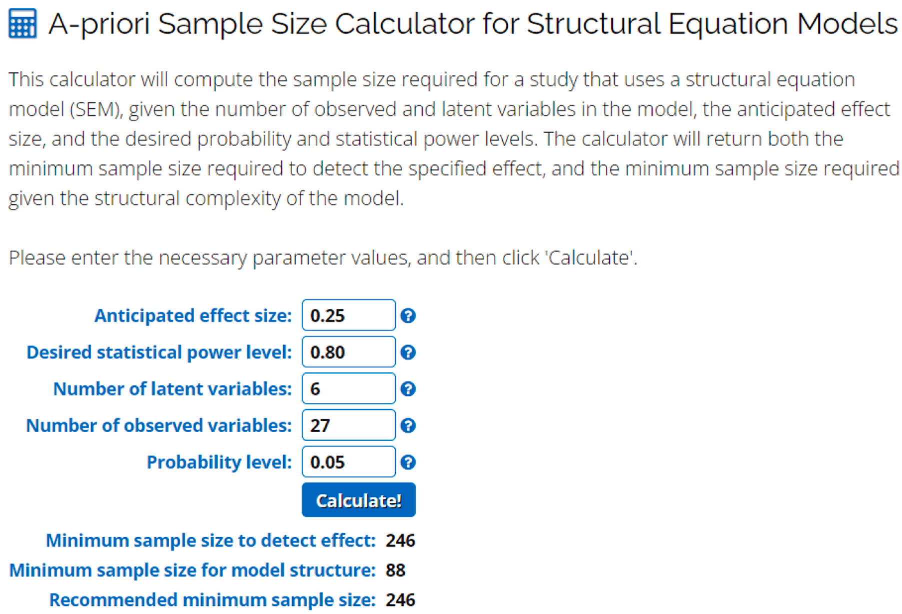

Fig. 2. A-priori sample size calculator for structural equation model [67].

the chi-square test results and X2/df ratio based on cutoff values proposed by Ayanwale and Ndlovu [73]. A value below 3 indicated a good fit, while a value between 3 and 5 suggested an acceptable fit. For RMSEA and SRMR, a value of $\leq$ 0.08 was considered good, and fit indices above 0.90 often indicated a satisfactory level of fit. Also, in our mediation analysis, guided by the methodology proposed by Oladipo-Abodunwa et al. [74], Nitzl et al. [75], and Zhao et al. [76] as depicted in Fig. 3, we explored various mediation scenarios. These scenarios included partial mediation (complementary mediation), competitive mediation, and full mediation (indirect-only mediation). Complementary mediation was identified when the indirect and direct effects were statistically significant and pointed in the same direction. This suggests that the mediator partially mediates the relationship between the exogenous and criterion variables, with both pathways contributing to the observed effect.

Competitive mediation emerged when both the indirect and direct effects were statistically significant but pointed in opposite directions. This dynamic indicates that the mediator enhances the relationship

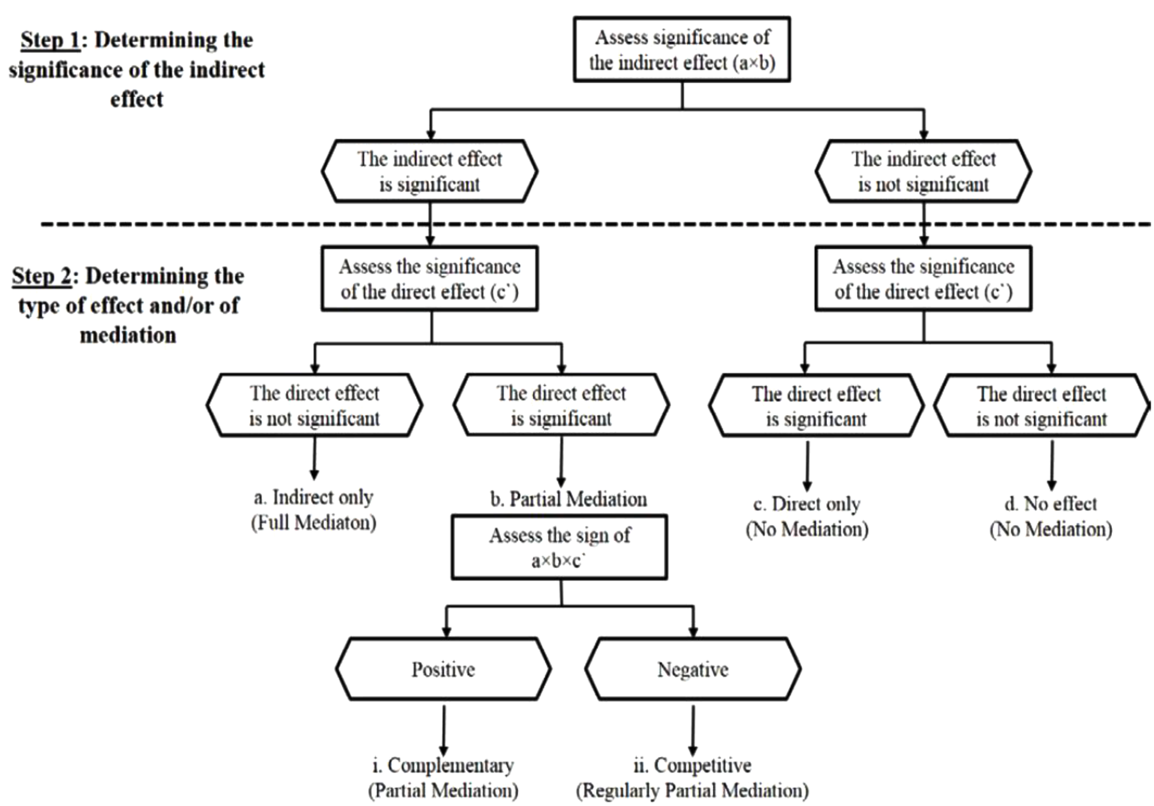

Fig. 3. Procedure for mediation analysis [76].

between the exogenous and criterion variables, but the total effect is mitigated due to the opposing directions of the direct and indirect effects. Indirect-only mediation, or full mediation, was evident when a significant indirect effect was observed, while the direct effect was not statistically significant. In such cases, the mediator fully explains the relationship between the exogenous and criterion variable, rendering the direct path non-significant when accounting for the mediator. Furthermore, the authors identified two types of non-mediation scenarios: In instances of direct-only non-mediation, the direct effect was statistically significant, indicating a direct relationship between the predictor and outcome variables. However, the indirect effect was not significant, suggesting that the mediator did not play a role in explaining the observed relationship. No-effect non-mediation occurred when neither the direct nor the indirect effect was statistically significant. In this scenario, the mediator did not contribute to explaining the relationship between the predictor and outcome variables, and the total effect was not observed. By considering these mediation and non-mediation scenarios, our analysis provided a comprehensive understanding of the complex interactions among variables, shedding light on the mechanisms through which the predictor influences the outcome, whether mediated or not.

3.5. Common method bias

We performed Harman's single-factor test to evaluate the possible presence of common method bias in our study due to self-reported data and a cross-sectional survey. If a single factor accounted for more than 50 % of the variability, it would suggest a potential issue of common method bias [77]. Our findings showed that the most influential factor explained approximately 13.47 % of the variability. Therefore, we can confidently state that common method bias is not a significant concern in this study.

4. Results

Table 3 provides insights into the relationships between the study constructs. Perceived usefulness (PU) is positively correlated with ease of use (EU) ($r = 0.302$, $p < 0.01$), technical skills (TP) ($r = 0.073$, $p < 0.05$), school support and resources (SSR) ($r = 0.407$, $p < 0.01$), attitude (AT) ($r = 0.379$, $p < 0.01$), and behavioral intention (BI) ($r = 0.427$, $p < 0.01$). In essence, teachers who perceive AI as beneficial are more likely to find it user-friendly, possess advanced technical skills, appreciate institutional support, foster a positive attitude, and intend to integrate AI into their teaching practices. This signifies a comprehensive impact of perceived usefulness on various facets of teachers' perceptions and intentions. Furthermore, EU is positively correlated with TP ($r = 0.455$, $p < 0.01$), SSR ($r = 0.435$, $p < 0.01$), and AT ($r = 0.577$, $p < 0.01$). This implies that teachers who find AI easy to use are likelier to have advanced technical skills, value institutional support, and exhibit a positive attitude towards AI. The results suggest that an intuitive and user-friendly AI system can positively influence teachers' technical skills and attitudes. TP positively correlates with SSR ($r = 0.463$, $p < 0.01$). This indicates that teachers with enhanced technical skills are more inclined to appreciate the support and resources provided by educational institutions. SSR positively correlates with AT ($r = 0.495$, $p < 0.01$). This suggests that adequate school support and resources contribute to a positive attitude among teachers regarding AI, highlighting the importance of institutional backing. AT positively correlates with BI ($r = 0.578$, $p < 0.01$). A positive attitude towards AI strongly predicts teachers' behavioral intention to use AI in their teaching practices. This underscores the significance of cultivating a positive mindset among teachers for successful AI adoption.

Also, multicollinearity is when two or more variables are highly correlated say 0.90 [78,79]. Table 2 revealed that correlation estimates among the constructs in the measurement model are all below the threshold of 0.90. Therefore, we conclude that there is no evidence of multicollinearity among the variables in this study. The normality tests conducted on the dataset (see Table 4) revealed that the Skewness values range from -1.422 to -0.154, while the Kurtosis values range from -0.994 to 2.213. To assess the normal distribution of the dataset, established criteria were applied: a dataset is considered normal if its Skewness value is between -2 and +2 [80] and its Kurtosis value is between -7 and +7 [78]. Based on the results and adherence to these criteria, we concluded that the dataset satisfies the conditions of univariate normality. Importantly, the Mardia test [81] was also used to assess the multivariate normality of the dataset. The MVN package [82] in the R programming language (v4.3.1; R [83]) was implemented for this purpose. The "mardia" argument in the mvnTest function of the MVN package was utilized to compute Mardia's multivariate skewness and kurtosis coefficients, along with their corresponding statistical significance. The R script for the analysis (result <- mvn(data = mySEMdata, mvnTest = "mardia"), and result$multivariateNormality) indicated that Mardia skewness returned (statistic = 39.443, $p = 0.192$), and Mardia Kurtosis returned (statistic = 7.294, $p = 0.206$). Since the p-values are above 0.05, we concluded that the dataset met the criteria for multivariate normality. These assessments confirm that the data fulfilled the necessary conditions for subsequent statistical analyses. Before delving into the mediation analysis, it is essential to confirm the reliability and validity of all construct measures, and ensure that the structural model satisfies all necessary quality criteria.

Additionally, Table 4 and Fig. 4 present standardized estimates, which are item loadings from the Confirmatory Factor Analysis (CFA). These values are above 0.50, as suggested by Ayanwale and Molefi [84] and Hair et al. [79], except for TP5 (TP5 = 0.402), which was removed from the model. Consequently, the results indicate a satisfactory measurement model with $X^2 = 477.088$; df = 280; p = 0.000, CMIN/df = 1.704, TLI = 0.947, GFI = 0.897, CFI = 0.954, NFI = 0.927, RMSEA = 0.047 [90 %CI, 0.040 - 0.055], and SRMR = 0.042, respectively.

Further, CFA was used to assess the reliability and validity of the constructs. The internal consistency of the scale measurements was evaluated using reliability indicators such as Cronbach's alpha (α) and composite reliability (CR). Generally, a high scale reliability is indicated when α and CR are above 0.70, while values above 0.6 suggest good reliability and values below 0.35 are considered low [36,85,86]. In this study, the overall Cronbach's α coefficient for the 27 items was calculated as 0.873, indicating high internal consistency. The individual constructs showed α values ranging from 0.813 to 0.871, and CR values ranged from 0.875 to 0.895, as shown in Table 5. These findings confirm good internal consistency and satisfactory reliability of the scale.

Furthermore, Table 5 presents the Average Variance Extracted (AVE)

Table 3
The mean, standard deviation and correlations of the study constructs.

Correlations	Mean	Std.	Skewness	Kurtosis	PU	EU	TP	SSR	AT	BI
PU	20.67	3.538	-.855	.412	1	.302**	-.073	.407**	.379**	.427**
EU	20.60	3.468	-.702	.224		1	.043	.455**	.435**	.577**
TP	20.27	5.096	-.340	-.462			1	.018	.017	.032
SSR	20.49	3.269	-.427	.091				1	.463**	.578**
AT	12.35	1.886	-.422	-.214					1	.495**
BI	16.06	2.625	-.292	-.476						1

** Correlation is significant at the 0.01 level (2-tailed).

Table 4
Standardized loadings and normality assessment.

Manifest variable			Standardized estimate	Skewness	Critical ratio	Kurtosis	Critical ratio
PU5	<—	PU_1	0,768	-0,852	-6,175	0,061	0,221
PU4	<—	PU_1	0,690	-1,139	-8,254	0,562	2,037
PU3	<—	PU_1	0,741	-0,777	-5,627	0,207	0,750
PU2	<—	PU_1	0,809	-1,422	-10,301	1,909	6,916
PU1	<—	PU_1	0,626	-0,671	-4,862	0,019	0,070
EU5	<—	EU_2	0,717	-0,803	-5,819	0,033	0,119
EU4	<—	EU_2	0,725	-0,865	-6,267	0,402	1,457
EU3	<—	EU_2	0,742	-0,644	-4,667	-0,393	-1,424
EU2	<—	EU_2	0,733	-0,692	-5,013	-0,069	-0,251
EU1	<—	EU_2	0,798	-0,825	-5,977	0,489	1,771
TP4	<—	TP_3	0,746	-0,154	-1,113	-0,994	-3,602
TP3	<—	TP_3	0,967	-0,350	-2,536	-0,867	-3,140
TP2	<—	TP_3	0,838	-0,357	-2,590	-0,697	-2,525
TP1	<—	TP_3	0,695	-0,905	-6,560	1,296	4,694
SSR5	<—	SSR_6	0,581	-1,273	-9,222	2,213	8,016
SSR4	<—	SSR_6	0,645	-0,998	-7,233	1,076	3,900
SSR3	<—	SSR_6	0,532	-0,525	-3,806	0,092	0,333
SSR2	<—	SSR_6	0,878	-0,546	-3,956	0,044	0,158
SSR1	<—	SSR_6	0,909	-0,383	-2,778	-0,491	-1,777
BI4	<—	BI_7	0,735	-0,730	-5,290	0,129	0,466
BI3	<—	BI_7	0,684	-0,529	-3,834	0,171	0,619
BI2	<—	BI_7	0,686	-0,471	-3,415	0,038	0,136
BI1	<—	BI_7	0,780	-0,548	-3,970	0,248	0,900
AT3	<—	AT_5	0,787	-0,410	-2,968	-0,522	-1,891
AT2	<—	AT_5	0,720	-0,232	-1,685	-0,377	-1,366
AT1	<—	AT_5	0,812	-0,600	-4,345	-0,242	-0,877

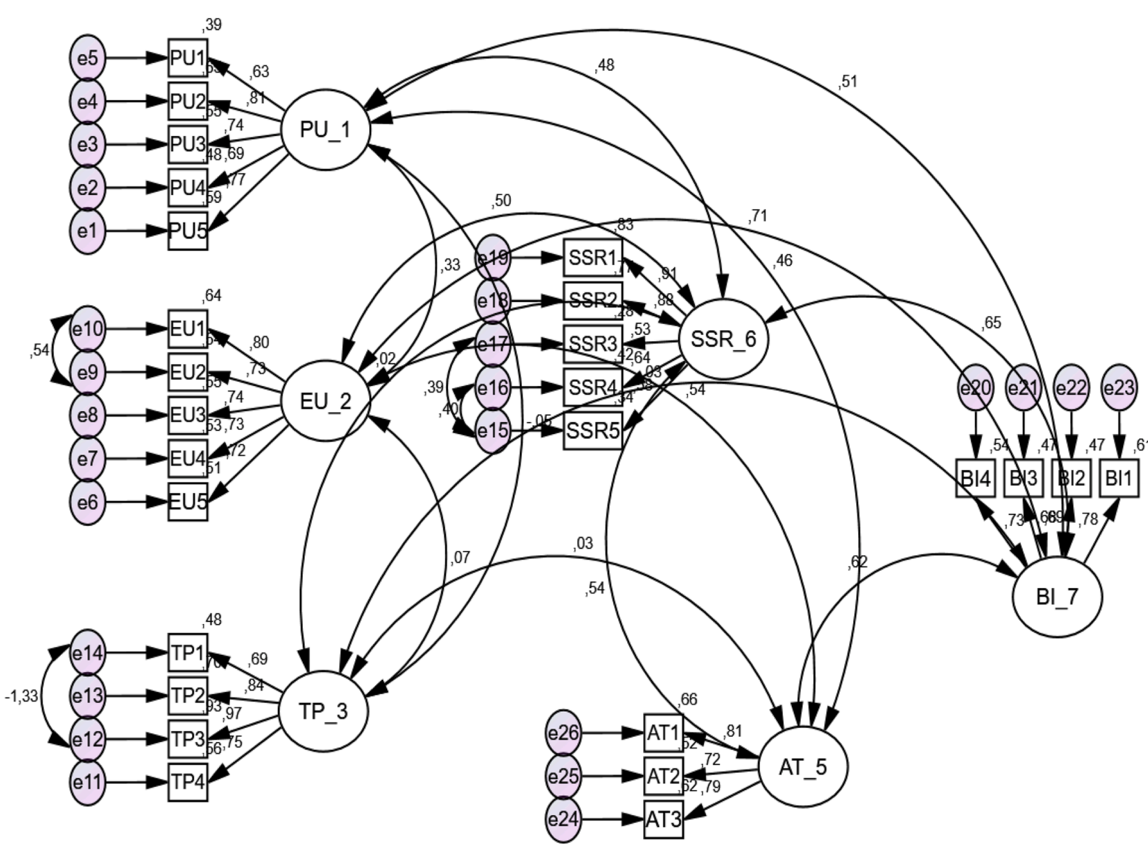

Fig. 4. CFA model.

for all constructs, which consistently exceeded 0.50. This suggests that the data demonstrated convergent validity for the study constructs [87]. To establish discriminant validity, the approach recommended by Ayanwale et al. [88] and Fornell and Larcker [87] was utilized. The square root of the AVE values was compared with their corresponding correlations, revealing that the square root of AVE consistently exceeded the corresponding correlations (see Table 5). This result further supports the discriminant validity of the study constructs.

Also, the results of our Structural Equation Modeling (SEM) analysis, shown in Fig. 5, display coefficients and their corresponding significance levels. The SEM results confirm that the model fits well with the data, as supported by various fit indices: $X^2 = 460.846$; df = 279; p = 0.000,

Table 5
Construct reliability and validity.

Constructs	α	CR	AVE	PU	EU	TP	SSR	AT	BI
PU	0.837	0.897	0.532	**(0.729)**					
EU	0.871	0.886	0.553	0.302	**(0.744)**				
TP	0.866	0.895	0.669	-0.073	0.043	**(0.818)**			
SSR	0.856	0.890	0.527	0.407	0.455	0.018	**(0.726)**		
AT	0.819	0.875	0.522	0.379	0.435	0.017	0.463	**(0.722)**	
BI	0.813	0.879	0.599	0.427	0.577	0.032	0.578	0.495	**(0.774)**

*The diagonal elements represent the square roots of the average variance extracted, while the off-diagonal elements denote the correlation estimates.

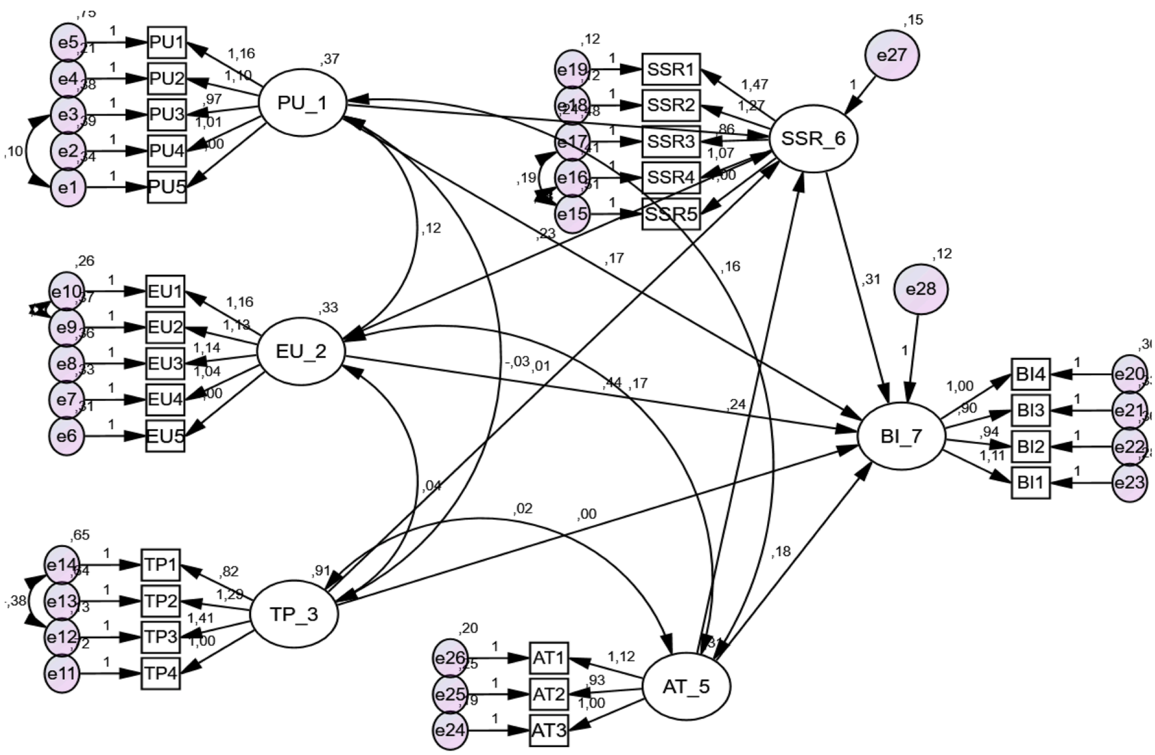

Fig. 5. A structural model with school support and resources as a mediator.

CMIN/df = 1.652, TLI = 0.951, GFI = 0.900, CFI = 0.958, IFI = 0.958, NFI = 0.901, RMSEA = 0.046 [90 %CI, 0.038 - 0.053], and SRMR = 0.041. Together, these indices indicate that the model effectively explains the data and sheds light on the relationships between variables.

In addition, to assess the significance of specific indirect effects and the overall indirect effect, we utilized a bootstrap routine in AMOS with 5,000 bootstrap subsamples. The 95 % bias-corrected percentile bootstrap confidence intervals in the final results allow us to determine significance. If the confidence interval values do not include zero, the effects are considered significant at the 5 % level. Conversely, if the values include zero, the effects are considered non-significant [89,90]. Consequently, Table 6 presents the results of the indirect impact of school support and resources within the proposed relationships.

The results in Table 6 outline the direct and indirect effects, along with confidence intervals and p-values, of the relationships among perceived usefulness (PU), perceived ease of use (EU), attitude (AT), technical proficiency (TP), school support and resources (SSR), and behavioral intention to use AI-driven technology (BI). The main focus is on the mediating role of school support and resources (SSR) in these connections. Table 6 demonstrates a significant indirect impact of perceived usefulness on in-service teachers' behavioral intention to use AI in their teaching practices, which is both positive and significant (b = 0.073, CI: 0.0024 - 0.156, p = 0.001), confirming H1. Additionally, the direct effect of perceived usefulness on in-service teachers' behavioral intention to use AI, in the presence of the mediator, was also found to be significant and positive (b = 0.173, p = 0.005). Therefore, it can be inferred that school support and resources partially mediate (i.e., have a complementary mediation effect) the relationship between perceived usefulness and teachers' behavioral intention to use AI-driven technology. Similarly, there is a positive and statistically significant indirect

Table 6
Summary of indirect effect relationship of school support and resources.

Relationships	Direct effect	Indirect effect	Confidence interval		P-value	Decision	Conclusions
			Lower bound	Upper bound			
PU_1 —> SSR_6 —> BI_7	0,173 (0,005)	0,073	0,024	0,156	0,001	H1 supported	Partial mediation (Complementary)
EU_2 —> SSR_6 —> BI_7	0,436 (0,000)	0,07	0,026	0,149	0,001	H2 supported	Partial mediation (Complementary)
AT_5 —> SSR_6 —> BI_7	0,182 (0,016)	0,075	0,025	0,161	0,001	H3 supported	Partial mediation (Complementary)
TP_3 —> SSR_6 —> BI_7	-0,003 (0,923)	0,002	-0,013	0,02	0.923	H4 not supported	No mediation

effect of perceived ease of use on behavioral intention (b = 0.070, CI: 0.026 - 0.149, $p = 0.001$), supporting H2. Moreover, the direct effect of perceived ease of use on behavioral intention in the presence of the mediator was also found to be significant and positive (b = 0.436, $p = 0.000$). Consequently, school support and resources partially mediate (i. e., have a complementary mediation effect) the relationship between perceived ease of use and teachers' behavioral intention to use AI-driven technology.

Furthermore, a significant indirect impact of attitude towards using AI on behavioral intention was observed, being positive and significant (b = 0.075, CI: 0.025 - 0.161, $p = 0.001$), supporting H3. The direct effect of attitude towards using AI on behavioral intention in the presence of the mediator was also found to be significant and positive (b = 0.182, $p = 0.016$). Hence, school support and resources partially mediate (i.e., have a complementary mediation effect) the relationship between attitude towards using AI and teachers' behavioral intention to use AI-driven technology. However, the direct effect from technical proficiency to behavioral intention was not found to be significant (-0.003, $p = 0.923$), and the indirect effect through SSR was also not statistically significant (b = 0.002, CI: -0.013 - 0.02, $p = 0.923$), not supporting H4. This suggests no mediation effect of school support and resources on the relationship between technical proficiency and behavioral intention. These findings highlight the crucial role of school support and resources for in-service teachers in connecting perceived usefulness, perceived ease of use, and a positive attitude to an intention to use AI-driven technology in teaching practices. To enhance teachers' inclination to use AI in their teaching, educational institutions should focus not only on fostering positive perceptions and attitudes but also on ensuring the provision of ample support and resources, including training, technological infrastructure, and other forms of assistance that facilitate the effective integration of AI into teaching methodologies.

5. Discussion

This study investigated in-service teachers' acceptance and use of AI-driven technology. Confirmatory Factor Analysis was used to validate constructs and test the validity and reliability of this study. A high internal consistency was reflected in Cronbach's α of 0.873 for 27 items, and individual constructs showed α values from 0.813 to 0.871 and CR values from 0.875 to 0.895, confirming good reliability. The study also showed convergent validity for the study constructs [87]. Additionally, the square root of the AVE values was compared with their corresponding correlations, and the discriminant validity was supported by the results. Through the SEM analysis, the study highlights the crucial role of school support and resources as a mediating variable in the relationships between the specific constructs of perceived usefulness, perceived ease of use, attitude, technical proficiency, and school support and resources. The findings support the notion that positive perceptions and attitudes alone may not be sufficient; adequate support and resources are necessary to facilitate the effective integration of AI into teaching methodologies. Consequently, this study examined the above-mentioned constructs and how they influence in-service teachers' acceptance and use of AI-driven technology in their teaching endeavors. The results show that there is a significant direct positive effect of perceived usefulness on behavioral intention, supporting H1. The indirect effect of PU on BI through the mediating variable of school support and resources is also found to be significant, confirming a complementary mediation effect.

Further, in Wang et al., [52]'s view, the observed correlation reinforces the existing understanding that teachers who perceive AI as beneficial are more likely to have a positive intention to integrate it into their teaching practices. Previous research has highlighted the critical role of perceived usefulness in shaping users' intentions to adopt technology [11,21,47]. On other line of thought, the present study adds empirical evidence to this by demonstrating a significant positive effect of SSR on perceived usefulness on in-service teachers' behavioral intention to use AI. This relationship between these variables suggests that for in-service teachers to have an intention to integrate and utilize AI- driven technology into their classes is in line with Rahiman and Kodikal [54] who maintain that the school plays an essential role in making sure that they provide in- service teachers with all the necessary AI- technological tools. Further, this implies that teachers' belief in the utility of AI alone may not guarantee adoption; the provision of SSR, including training and support, is crucial. Moreover, previous research has emphasized the importance of teachers' perception of the ease of use of AI and behavioral intention [11]. It is crucial to note that these constructs are influenced by the support and resources provided by the school. Hence, the study's findings align with this perspective. Thus, similar to PU, there is a significant direct positive effect of perceived ease of use on behavioral intention. Also, the indirect effect of EU on BI through SSR as the mediator is also confirmed to be significant, indicating a complementary mediation effect, supporting H2. Consistent with prior literature stressing the importance of teachers' perceptions of the ease of employing AI [23,55], the present study establishes a significant direct effect of perceived ease of use on in-service teachers' behavioral intention to use AI. This suggests that the school providing trainings that equip the in- service teachers on how to use AI technologies is vital. If the in-service teachers find AI- driven technology to be user- friendly and effortless to be used, their acceptance and use of AI in their classroom practices is likely to increase.

Additionally, the study finds a significant indirect effect of AT on BI through SSR mediator indicating a complementary mediation effect and therefore, supporting H3. The positive and significant link between attitude towards using AI and behavioral intention is consistent with literature suggesting the impact of attitudes on technology adoption [1,21]. Building upon the established relationship between attitude and intention to use AI technology [47], van Twillert et al. [60] collaborates the results of this study which underscores the role of school support and resources in mediating the relationship between attitude and intention to use AI. This correlation denotes the significance of cultivating a positive mindset among teachers for the successful adoption of AI in educational settings. It can also be argued that this link between these variables reaffirms the literature's assertion that institutional backing is crucial for shaping teachers' attitudes towards AI-driven technology [60]. In contrast to other constructs, the direct effect of technical proficiency on behavioral intention is not found to be significant in this study. Additionally, the indirect effect through SSR mediating variable is also not statistically significant, not supporting H4. This is diverging from the literature which suggests the importance of technical skills in technology adoption. Technical proficiency has been highlighted as a crucial factor in AI- driven technology adoption [62,61]. This implies that this study does not observe a significant direct effect, suggesting that other factors may play a more substantial role in determining behavioral intention to use and accept AI- driven technology in schools. Succinctly, it was be concluded that SSR plays an important role in making sure that in-service teachers use and accept AI in their teaching practices. As a result, it is beneficial for schools to provide training, equip their teachers on how effectively they can use this technology to improve the teaching and learning of learners.

6. Theoretical contributions of the study

This study significantly contributes to the theoretical understanding of technology adoption in education, specifically in relation to integrating AI into teaching practices. First, it expands upon the Unified Theory of Acceptance and Use of Technology (UTAUT) framework by including additional variables such as technical proficiency, school support, and resources. This deepens our understanding of the factors influencing teachers' intention to use AI-driven technology in educational parlance. Furthermore, the study emphasizes the mediating role of school support and resources in shaping teachers' perceptions and intentions regarding AI integration. By highlighting the importance of institutional support, the study provides insights into how organizational factors interact with individual perceptions to drive technology adoption efforts. The study identifies various scenarios through mediation analysis, including partial, competitive, and full mediation, which shed light on how school support and resources impact teachers' intention to use AI. These findings offer nuanced insights into the interaction between individual perceptions and organizational factors in technology adoption. Additionally, the study contributes to the empirical validation of key constructs such as perceived usefulness, perceived ease of use, technical proficiency, school support and resources, attitude, and intention to use AI in education. By utilizing rigorous measurement and validation techniques, the study enhances the reliability and validity of these constructs, thereby strengthening the theoretical foundations of technology adoption research.

7. Practical implications of the study

The findings of this study provide practical insights that can greatly support teachers in Lesotho as they integrate AI into their teaching methods. Building on previous research that has emphasized the importance of tailored professional development initiatives [21], our study highlights the need for ongoing training programs designed to enhance teachers' abilities in using AI-driven technologies. These programs should not only focus on technical aspects but also emphasize practical implementation in various teaching scenarios. Collaborative learning communities have been shown to be beneficial in promoting knowledge sharing and boosting teachers' confidence in adopting new technologies [47]. Therefore, it is recommended to create such communities where teachers can exchange experiences, insights, and best practices related to AI integration.

In-service teachers, in collaboration with relevant educational associations, have the opportunity to advocate for policies that prioritize the integration of AI in education. This is consistent with previous literature stressing the importance of policy support in fostering technology adoption [60]. Actively participating in policy dialogues and contributing insights allows teachers to shape frameworks that promote responsible and efficient use of AI in teaching. School leaders play a crucial role in supporting teachers by providing encouragement, recognizing their efforts, and addressing any concerns or challenges that may arise during the implementation of AI technologies [55]. Encouraging exploration of AI tools that facilitate inclusive learning strategies is also recommended, in line with the literature highlighting the potential of AI to accommodate diverse learning styles [23].

Furthermore, teachers can actively collaborate with technology providers by participating in discussions on the development and improvement of AI tools. By providing feedback on usability, functionality, and alignment with local contexts, teachers contribute to the refinement of AI solutions that meet their specific needs [1]. Prioritizing ethical considerations related to AI use in education is crucial, as highlighted by Hagendorff [62]. This includes addressing concerns such as data privacy, fairness, and potential biases inherent in AI algorithms. Teachers can incorporate responsible AI practices into their teaching methods, contributing to the ethical discourse surrounding AI use in education. Given the constantly evolving nature of technology, in-service teachers should embrace a mindset of continuous learning and adaptation. Staying updated on AI advancements, engaging in online communities, and participating in professional development opportunities empower teachers to enhance their skills in integrating AI [47]. By embracing these practical suggestions, teachers can navigate the complexities of AI integration in education and harness its potential to enhance teaching and learning outcomes.

8. Conclusions

One of the significant findings to emerge from this study is the existence of a positive correlation between various key constructs related to the adoption of AI among in-service teachers. The results indicate that perceived usefulness has a significant impact on teachers' perceptions and intentions, demonstrating positive correlations with ease of use. This finding suggests that teachers' positive perception of AI's usefulness contributes to their belief that the technology is easily accessible and can be incorporated into their teaching practices. Also, teachers who view the use of AI technology as beneficial are more inclined to be motivated to acquire or enhance their technological skills. Teachers who perceive AI as useful are more likely to value school support and resources. Additionally, they are more likely to possess a positive attitude towards integrating AI into their educational practices. Finally, teachers who recognize the usefulness of AI are more inclined to express a concrete intention to incorporate it into their teaching methods. Overall, these findings highlight the complex impact of perceived usefulness on teachers' perceptions and intentions, depicting positive correlations with ease of use, technical skills, school support and resources, attitude, and behavioral intention. This research also provides valuable insights into the interconnected nature of the highlighted factors in shaping teachers' perceptions of AI. As the world today witnesses the emergence of AI tools in education and the promising initiatives concerning AI integration in education in Sub-Saharan countries [42], it is important for technology designers, particularly those involved in AI systems, to understand teachers' perspectives and requirements to fully unlock the potential benefits of these AI innovations. The insights gained from teachers' perceptions can shed light on how AI can enhance academic achievements and promote educational equity.

Moreover, the findings of the mediation analysis reveal that when teachers perceive AI as beneficial, it not only facilitates their ease of use but also motivates them to enhance their technical skills. Additionally, the positive perception of AI among in-service teachers is also linked to the support and resources provided by the school, along with a positive attitude towards AI integration in teaching. In other words, in-service teachers are more likely to view AI positively when they feel supported by the school and have access to necessary resources. Furthermore, such teachers are more likely to develop a positive attitude towards incorporating AI into their teaching practices. Ultimately, in-service teachers who perceive AI as useful are more likely to express their intention to utilize it in their teaching practices. The crucial role of school support and resources is supported by the current findings, which acts as a connecting link between teachers' perception of AI's usefulness and their actual intention to use it. These findings offer empirical evidence regarding the role of support and resources provided by schools in strengthening the positive relationships between perceived usefulness, ease of use, and attitude, thereby increasing teachers' willingness to adopt AI in their teaching practices. Prior to the present study, there was limited evidence supporting the notion that school support and resources positively impact the likelihood of teachers incorporating AI in their teaching. Currently, the contribution made by this study will assist schools and policymakers in formulating strategies to support teachers and provide resources that promote the sustainable adoption of AI in the education sector. Lastly, insights gathered from the demographic characteristics of the respondents suggests a gender imbalance that should be considered when implementing AI-driven technology, considering potential gender-specific preferences and needs to ensure inclusivity in educational technology initiatives. Special attention should also be given to older respondents to ensure effective adoption and training tailored to their needs. Efforts should be directed towards addressing potential gaps in technology access, particularly for respondents from rural backgrounds. There is a need to emphasize training programs that cater to respondents with varying levels of technological proficiency, ensuring that teachers feel adequately prepared to leverage AI tools effectively.

9. Limitations and future works

The study has limitations that should be considered when interpreting its results. Firstly, it is limited to Lesotho, which may affect the generalizability of the findings to teachers in other regions. Future research should include diverse geographical locations to provide a more comprehensive perspective. Additionally, the study's sample size may not fully represent Lesotho's diverse population of in-service teachers. A more extensive and diverse sample could enhance the robustness of the study. The cross-sectional design also limits the exploration of changes over time, and a longitudinal approach in future studies would be valuable. Furthermore, relying on self-reported data may introduce social desirability bias. Future investigations could benefit from a multi-method approach, including observations and interviews. The study acknowledges the importance of technical proficiency but does not thoroughly explore teachers' actual technical skills with AI tools. A more in-depth investigation is needed to understand teachers' readiness for AI integration. The measurement of school support and resources as a mediating variable may lack granularity. Comparative studies across countries or regions could provide insight into cultural influences on teachers' acceptance of AI. Qualitative research, such as in-depth interviews, could provide a nuanced understanding of teachers' perceptions and experiences with AI. Lastly, exploring teachers' ethical awareness when using AI is important for future research. By addressing these limitations and pursuing these future research avenues, we can gain a more comprehensive understanding of AI acceptance in education, particularly among in-service teachers in Lesotho and beyond.

Institutional review board statement

All respondents provided informed consent before they participated in the study. The study was conducted following the guidelines outlined in the Declaration of Helsinki and was approved by the Ethics Committee of the National University of Lesotho.

Funding

This research received no external funding.

Data availability statement

The dataset used in this research is strictly available upon request from the corresponding author.

CRediT authorship contribution statement

Rethabile Rosemary Molefi: Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Musa Adekunle Ayanwale:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lehlohonolo Kurata:** Writing – review & editing, Writing – original draft, Conceptualization. **Julia Chere-Masopha:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Acknowledgment

We would like to express our sincere gratitude to all those who contributed to the completion of this study. We greatly appreciate the cooperation and participation of the in-service teachers in Lesotho who generously shared their experiences and perspectives. We would also like to thank the Ministry of Education and Training for their support. Your collective contributions have played a crucial role in the successful completion of this research.

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