Journal of Information Technology Education: Research

An Official Publication of the Informing Science Institute
InformingScience.org

JITEResearch.org

Volume 24, 2025

A MODEL FOR THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN INCLUSIVE EDUCATION: AN EXPLORATORY STUDY OF KEY FACTORS AND EXPERT INSIGHTS

Kok Weng Ma	Sunway University, Petaling Jaya, Malaysia	makokweng2001@gmail.com
Rexado Pramudita Julianton	Sunway University, Petaling Jaya, Malaysia	rexado.pramudita@gmail.com
Xian Yang Chan	Sunway University, Petaling Jaya, Malaysia	xanthus930@gmail.com
Yong Teng Chai	Sunway University, Petaling Jaya, Malaysia	yongteng3366@gmail.com
Muaadh Mukred*	Sunway University, Petaling Jaya, Malaysia	muaadhm@sunway.edu.my
Mikkay Wong Ei Leen	Sunway University, Petaling Jaya, Malaysia	mikkayw@sunway.edu.my
Abdu H. Gumaei	Prince Sattam bin Abdulaziz University, Al-Kharj, Saudi Arabia	a.gumaei@psau.edu.sa

* Corresponding author

ABSTRACT

Aim/Purpose — This study adopts a mixed-method approach to examine the factors influencing the adoption of AI-based assistive technologies among students with special needs. Specifically, it explores the roles of social support, motivation, digital literacy, and self-efficacy in shaping students' perceptions and behavioral intentions toward these technologies within inclusive education settings.

Accepting Editor Joko Slamet | Received: May 3, 2025 | Revised: July 27, August 5, August 21, 2025 | Accepted: August 23, 2025.
Cite as: Ma, K. W., Julianton, R. P, Chan, X. Y., Chai, Y. T., Mukred, M., Wong Ei Leen, M., & Gumaei, A. H. (2025). A model for the adoption of artificial intelligence in inclusive education: An exploratory study of key factors and expert insights. *Journal of Information Technology Education: Research, 24,* Article 27.
https://doi.org/10.28945/5612

Background	The integration of assistive technologies into inclusive learning environments has gained significant attention due to its potential to improve educational outcomes for students with disabilities. Despite this growing interest, limited empirical research has explored the determinants of such technologies' adoption, particularly through the technology acceptance model lens. This study addresses this gap by extending the technology acceptance model framework to incorporate additional constructs such as social support, motivation, digital literacy, and self-efficacy, offering a more comprehensive understanding of user acceptance in inclusive contexts.
Methodology	A mixed-method design was employed. The quantitative phase involved a survey of 118 students enrolled in six inclusive education programs across Saudi Arabian universities. Data were analyzed using structural equation modeling via SmartPLS to examine the relationships between the proposed constructs. Complementing this, the qualitative phase included in-depth interviews with eight AI experts specializing in assistive technologies for students with disabilities, providing contextual insights and validating the quantitative findings.
Contribution	This study advances the technology acceptance model by integrating key psychological and social variables (social support, motivation, digital literacy, and self-efficacy) into the adoption framework. Doing so offers a more nuanced perspective on how students with special needs interact with and perceive AI-based assistive tools, addressing a critical gap in current inclusive education research.
Findings	The findings from the quantitative analysis indicate that social support and motivation significantly enhance perceived usefulness, while digital literacy and self-efficacy significantly enhance perceived ease of use. Both usefulness and ease of use substantially affect intention toward adopting assistive technology. Additionally, the qualitative findings reveal key themes emphasizing user-friendly designs, contextual adaptability, ethical considerations, and AI's potential to promote student autonomy.
Recommendations for Practitioners	Expert interviews underscore the necessity for ongoing professional development among educators to effectively implement assistive AI tools. Furthermore, fostering partnerships between technology developers and educators is critical for designing tools that meet the real-world needs of inclusive classrooms.
Recommendations for Researchers	By extending the technology acceptance model, this study opens new avenues for future research into other influencing factors, such as institutional readiness, cultural considerations, and policy support. Researchers are encouraged to apply this enriched model in various educational and geographical contexts to further validate its applicability.
Impact on Society	Understanding the factors that influence the adoption of assistive technology is essential for fostering inclusive and equitable education systems. This study contributes to the development of policies and implementation strategies that ensure students with disabilities can fully benefit from emerging educational technologies.
Future Research	Future studies can expand the scope of this research by exploring different educational settings, conducting longitudinal studies to assess long-term adoption trends, and incorporating additional stakeholders, such as parents and policymakers, to gain a more comprehensive understanding of assistive technology integration.

Keywords artificial intelligence assistive technologies, inclusive education, technology acceptance model, digital literacy, special needs students

INTRODUCTION

Amidst the surge of current technological innovations, artificial intelligence (AI) is a notable technology that has been transforming industries and societal structures with its robust potential (Chiu et al., 2024). Specifically, AI in the education field appears to present the possibility of being able to address and resolve challenges that students with disabilities often face and to promote their inclusivity and equity (Scott et al., 2025). More importantly, AI integration into inclusive education goes beyond technological development by touching upon the ethical aspects, which are imperative to destroy barriers and pave the way to future learning of all types of students, even those with disabilities (Salhab, 2025).

In the education field, the evolution of AI can be traced back to the mid-20th century, initiated by the conceptualization of machines that have the ability to mimic human cognition and decision-making (Patel & Indurkhya, 2025). The term AI was first introduced at the Dartmouth Conference in 1956, after which the computer-assisted instruction (CAI) systems emerged in the 1960s and 1970s, ultimately leading to AI's progression as a tool for personalized learning (Mishra, 2025). Legislative-wise, the Education for All Handicapped Children Act of 1975, later renamed as the Individuals with Disabilities Education Act (IDEA), laid down the commitment to inclusive education and boosted technology integration into learning environments (Grant, 2018; Roberts, 2022).

The past few decades witnessed several AI advancements in the form of machine learning, natural language processing (NLP), and computer vision, allowing the development and creation of adaptive learning platforms, assistive devices, and real-time accessibility solutions (Almufareh et al., 2024; Eziamaka et al., 2024). However, regardless of the above developments, AI's potential for transforming inclusive education remains underexplored, as evidenced by the gaps in its application and understanding, culminating in its lack of adoption (Holmes et al., 2022).

A notable development is the examination of decentralized AI systems to leverage computing enhancements of accessibility and privacy. Through decentralized AI, localized adaptive educational tools that are tailor-made to the students' needs can be delivered with minimized dependence on centralized internet infrastructure. Such a technique enhances data security and ensures that students in locations with low internet access can have high access to AI-driven resources. Discussions abound regarding the exploration of AI's role in education, but a specific focus on its applications in special education is still lacking (Kumari, 2025).

An attempt to connect theoretical insights with practical applications can address critical gaps in AI adoption literature in the context of inclusive education. Along this line of argument, empowering educators, policymakers, and developers with effective strategies is a must for implementing technologies that provide learning services to various learning needs. This has the potential to transform educational landscapes and ensure that students with disabilities can fully immerse themselves in inclusive, equitable, and technologically advanced learning processes.

In this paper, the contents are organized in the following systematic way. Following the introduction, the second section contains a review of relevant literature in a comprehensive look at current studies and theoretical foundations that are dedicated to the adoption of AI tools in inclusive education. This is followed by the third section, which presents the adopted study methodology with a detailed explanation of the mixed-method approach, data collection methods, and analysis procedures adopted to achieve the objectives. The fourth section explains the development of the extended TAM, followed by the development of the research hypotheses. In contrast, the fifth section discusses the results of the quantitative and qualitative analyses, shedding light on the significant findings from the structural

model and the interview session results. The sixth section presents the findings, implications, and related data insights, drawing on the perspectives gathered from the interviewed experts. Lastly, the seventh section summarizes the study's contributions, practical implications, theoretical advancements, and directions for future studies.

LITERATURE REVIEW

AI IN INCLUSIVE EDUCATION: EMERGING TRENDS AND OPPORTUNITIES

Recent advances in machine learning and NLP have led to transformative changes in educational practices, especially in inclusive settings. Tools such as adaptive learning platforms, emotional AI, and text-to-speech technologies are being increasingly used to support students with disabilities (Eziamaka et al., 2024; Oyedokun, 2025). Emotional AI, for instance, facilitates real-time identification of student frustration or disengagement, enabling personalized instructional responses (Lin & Chen, 2024). These tools are no longer experimental but are increasingly embedded in formal learning environments.

While many scholars highlight the promise of AI in promoting student agency and enhancing communication (Rice & Dunn, 2023; Sethi & Jain, 2024), there is growing concern about the framing of students with disabilities. AI systems are often designed from deficit perspectives, portraying students as problems to be managed rather than empowered agents in their learning (Rice & Dunn, 2023). This critique underscores the need for participatory, culturally sensitive approaches in AI tool development, especially in inclusive education.

ASSISTIVE TECHNOLOGIES, AI, AND THE ROLE OF ADOPTION MODELS

Studies such as Opoku et al. (2023) have applied the TAM to explore factors affecting educators' intention to adopt assistive technologies. While PEU and SE were found to influence behavioral intention significantly, PU was less impactful, highlighting adoption's complex, context-dependent nature. This nuanced finding contrasts with other studies (e.g., Bressane et al., 2024; Chalkiadakis et al., 2024), that emphasize the central role of usefulness in adoption, especially when AI systems support personalized interventions for cognitive or sensory impairments.

Despite the rising popularity of TAM and UTAUT frameworks, existing studies often omit essential social and psychological factors such as social support, motivation, and DL (Lee et al., 2025), factors especially relevant in inclusive educational environments. These omissions suggest that technology adoption models need to be expanded to account for the unique contexts of students with disabilities (Al-kfairy et al., 2024), whose learning often involves a broader network of support and customized interactions with technology.

Moreover, in inclusive education settings, adoption decisions are closely linked to pedagogical principles that prioritize student agency, differentiated instruction, and equitable participation (Li & Ruppar, 2021). Assistive technologies must not only be easy to use but must also align with inclusive pedagogical strategies such as Universal Design for Learning (UDL) and culturally responsive teaching (Zaugg, 2025). Understanding technology adoption in these contexts requires attention to how AI tools support personalized learning, foster student engagement, and enhance communication between teachers and diverse learners. Therefore, expanding traditional models to include pedagogical and relational factors offers a more holistic understanding of technology integration in inclusive classrooms.

INCLUSIVE EDUCATION IN SAUDI ARABIA: DEVELOPMENT AND CONTEXT

The development of inclusive education in Saudi Arabia has undergone a significant transformation over the past two decades, aligning with broader educational reforms under national initiatives such as Vision 2030. Initially, students with disabilities were primarily educated in specialized centers or

segregated settings; however, recent policy shifts have emphasized greater integration within mainstream schools (Alnahdi, 2020). The Ministry of Education has introduced multiple frameworks promoting inclusive practices, focusing on accessibility, teacher training, curriculum adaptation, and the provision of assistive technologies (Alsolami, 2024). Despite these advancements, challenges remain, particularly regarding teacher preparedness, infrastructure, and societal attitudes toward disability (Alqahtani et al., 2023). Research indicates that while there is strong governmental commitment to inclusion, practical implementation often varies across regions and institutions (Abu Mukh et al., 2024; Darwish, 2025).

Recent efforts have also begun exploring the role of emerging technologies, including AI-driven tools, to support differentiated instruction and enhance accessibility for students with disabilities (Alzahrani, 2025; Sulaimani & Bagadood, 2023). In this regard, Almalky and Alwahbi (2023) conducted a study to assess Saudi teachers' knowledge and experience with inclusive education practices. Surveying 125 teachers, the majority reported sufficient experience in inclusive teaching, irrespective of gender, training, education level, or school level. Notably, special education teachers indicated more experience than their general education counterparts. In a similar study, Alsolami (2025) demonstrated that AI-based interventions can significantly improve academic skills among students with mild intellectual disabilities in Saudi Arabia, offering empirical support for the educational benefits of AI in inclusive settings.

While prior research in the Saudi context presents encouraging evidence of the potential of AI to enhance learning outcomes for students with disabilities, it is often constrained by methodological limitations such as narrow sample representation, short intervention durations, and limited generalizability. Despite these challenges, the studies highlight the growing relevance of AI in supporting inclusive education. Building on this foundation, the present study aims to examine the key factors that influence the adoption of AI-based assistive technologies, specifically focusing on social support, motivation, DL, and SE within the context of inclusive education in Saudi Arabia.

Benefits, Challenges, and Ethical Dimensions of AI in Inclusion

There is robust evidence supporting the benefits of AI for enhancing accessibility and learning outcomes (Kumari, 2025). Meta-analyses such as those by L. Zhang et al. (2024) demonstrate positive effects of AI interventions – including robotics, VR, and intelligent software – on academic and social-emotional development among students with disabilities. Similarly, studies focused on specific communities, such as the deaf (Coy et al., 2025) and blind learners (Almurayziq et al., 2022), reveal that AI-driven systems can bridge communication gaps and personalize content delivery through voice recognition, gesture translation, and interactive avatars.

Yet, these advances are tempered by significant implementation barriers (Pierrès et al., 2024). Common challenges include high costs, limited teacher preparedness, inadequate infrastructure, and ethical concerns such as algorithmic bias and data privacy (Chalkiadakis et al., 2024; ZainEldin et al., 2024). In many cases, educators are not trained to use AI tools effectively, and students are not involved in the design or adaptation of technologies meant to support them. This further reinforces the argument that inclusive AI development must involve users (students, caregivers, and teachers) as co-designers (Coy et al., 2025; Rice & Dunn, 2023).

From a pedagogical perspective, effective integration of AI in inclusive education must go beyond technical deployment to consider how these tools enhance student-centered learning, autonomy, and collaboration (Ali, 2024; Almuhanna, 2025). Training programs must not only build technical capacity but also support teachers in embedding AI meaningfully within inclusive instructional practices (J. Zhang & Zhang, 2024). Ethical considerations, such as fairness, transparency, and respect for learners' diverse experiences, must be foregrounded to ensure that AI serves as an instrument of empowerment rather than exclusion (Almufareh et al., 2024). These pedagogical priorities are essential to advancing both the ethical and educational potential of AI in diverse learning environments.

Research Gaps and the Need for an Expanded Model

Despite the promising developments in AI for inclusive education, significant gaps remain. Few studies examine how students themselves perceive and adopt assistive AI technologies. Even fewer incorporate mixed-method approaches that capture behavioral trends and deeper experiential insights. Most studies focus on educators or technologists, neglecting the students' agency and interaction with the tools.

Furthermore, widely used theoretical models like TAM have not been sufficiently adapted to inclusive education contexts. The roles of social support, motivation, DL, and SE, while central to technology use in special needs education, remain underexplored in quantitative models. Our study addresses this gap by extending the TAM framework with these constructs and validating the model through quantitative and expert qualitative data.

Model Development

The process of model development in this study is geared towards obtaining an understanding of the integration of AI in inclusive education. This entails the development of a conceptual framework that houses the influencing factors of AI adoption and its effect on educational outcomes among students with disabilities. This method is based on the TAM and its extension through the addition of external variables that are related to inclusive education.

The developed model contains the examined constructs of PU, PEU, and intention to use AI technologies that TAM supports, in addition to which, external variables of social support, DL, SE, and motivation were added to encapsulate distinct challenges and enablers of AI adoption in inclusive learning environments. More specifically, social support stresses the role of collaborative networks such as peers, instructors, and family members – all of whom boost the use of AI. At the same time, DL represents the importance of technological competence in handling AI tools. In addition, SE represents the confidence of the individual in using the AI tools and technologies in an effective manner, whereas motivation represents both intrinsic and extrinsic factors driving the inclination of the students towards AI-driven solutions engagement.

To reiterate, data for model testing were gathered using structured surveys and interview sessions, after which the data obtained through the study were analyzed using SEM. This test determines relationships between variables and assesses the predictive power of the model. Such a statistical method culminates in robust findings and explains the constructs' interdependencies with each other.

One of the expectations from the final model is the presentation of actionable insights into the factors that drive or prevent AI adoption in inclusive education. The model's examination of technological and human-centric dimensions is directed towards developing effective AI solutions that contribute to enhanced learning experiences among students with disabilities. The findings are expected to assist stakeholders, including educators, policymakers, and developers, in developing strategies that connect the potential of the technology and its practical applications, ensuring that AI-assisted education is characterized by its inclusivity, equity, and transformative aspects.

Conceptual Model

The conceptual model's design is rooted in the TAM, and it is generally used to examine the factors that influence the adoption of AI tools in inclusive education. Aside from TAM variables, the model includes four major external variables, namely social support, motivation, DL, and SE, to test their effects on PU and PEU, and in turn, the latter's influence on intention to use AI tools among students with disabilities. The model proposes that SS and motivation affect PU (H1 and H2), while DL and SE affect PEU (H3 and H4). The model also proposes that PU and PEU significantly affect the intention to use AI (H5 and H6). The model represents a comprehensive framework for explaining the interconnections between individual, social, and technological factors when it comes to driving

AI technologies adoption in educational settings, primarily among students with disabilities. The proposed conceptual model is presented in Figure 1.

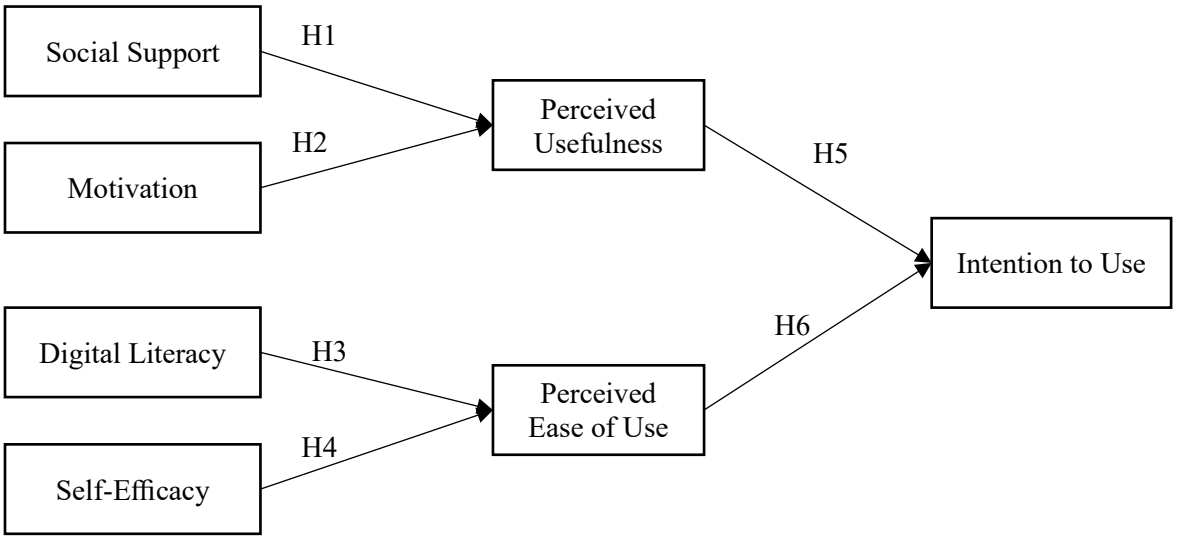

Figure 1. Conceptual model with hypotheses

HYPOTHESES FORMULATION

The formulation of the hypotheses portion of the study presents two major expectations concerning special needs students' intention towards AI technology use. In the first expectation, the focus is on users' perceptions, which indicates that PU and ease of use have significant effects on intention towards AI technology use, considering AI is viewed to enhance students' academic performance and productivity. In the second expectation, the positive effects of SS and motivation on usefulness and the effects of DL and SE on PEU are proposed. Overall, the proposed hypotheses create a comprehensive framework to examine the factors driving AI adoption among students with disabilities.

Social support

SS represents the AI tools that can be leveraged by disabled or special needs students to receive personalized assistance and adaptive learning plans, and it also represents assistive technologies that are created to meet individual needs (Hong & Kim, 2024). Such tools contribute to the enhancement of accessibility and offer various features like text-to-speech, chatbots that provide emotional support, and communication aids for the promotion of inclusivity. In addition, the tools, particularly learning analytics, keep track of the learning progress of the students, present interventions, and help instructors in providing tailor-made teaching strategies for students (Elshazly, 2025).

In a relevant review, Neeharika and Riyazuddin (2023) explored the effect of AI on assistive technologies among special needs children. Their work presented a discussion of different disabilities of the students, the current assistive technologies, and AI-directed support for learning development. It also touched upon future assistive technologies and related ethical concerns. They mentioned the role of AI in leading innovations like simulated environments fitted with augmented and virtual reality, enhanced visual tracking, social skills, and time management for disabled students. Thus, AI has the ability to transform learning and to tackle challenges.

More importantly, SS forms the attitudes and behaviors of students towards adopting technology, and thus stresses the importance of their perceptions in their intention towards technology use (Zhou, 2017). This aligns with TAM, where external factors such as SS indirectly influence behavioral

intention through PU and PEU (Venkatesh & Davis, 2000). Therefore, its integration into the conceptual model reflects its theorized role as a key antecedent of PU in AI adoption for inclusive education.

As for the effect of SS on the PU of AI technology, this study hypothesizes that:

H1: SS has a positive impact on PU of AI technology among special needs students.

Motivation

According to Venkatesh et al. (2012), hedonic motivation has a significant effect on the PU of AI technology, and in this case, among disabled students. Motivation represents the pleasure and enjoyment obtained from the use of technology, which improves their perception of the ability of AI to enhance their learning performance and their completion of learning tasks. A significant, albeit lesser, influence from motivation was revealed in comparison to other factors, but this does not minimize the outcome that hedonic motivation promotes a positive intention towards technology use among students, as evidenced by Yin et al. (2024).

Past studies also revealed that using AI tools motivated the inclination of the students to engage in learning, and this held true for students with special needs (Lai et al., 2023; Torres et al., 2023). AI applications are interactive and dynamic in attracting the interest of students and promoting their enjoyment and effective learning during their educational process (Khosravi et al., 2022). Teachers and parents are aware of the potential of AI tools to develop the skills of students with disabilities, developing their social, cognitive, and communication abilities. In addition, such tools furnish data-driven information, allowing educator and parent circles to oversee the students' progress, determine the challenges they face, and reach decisions based on accurate information, relating to their tailor-made learning plans, promoting collaboration and providing a supportive educational ecosystem for students having various and distinct needs (Heeg & Avraamidou, 2025; Jabali & Ayyoub, 2024). Within the TAM, motivation, as an external variable, has been shown to influence PU by shaping students' positive attitudes toward adopting new technologies (Venkatesh et al., 2003). Therefore, its inclusion in this conceptual model reflects its theorized role as a psychological factor driving the perceived utility of AI tools in inclusive education settings.

Thus, motivation is proposed to have a significant effect on the PU of AI with the following hypothesis;

H2: Motivation has a positive effect on the PU of using AI technology among special needs students.

Digital literacy

This variable represents the effective and critical ability to navigate, evaluate, and create information with the help of various digital technologies. The concept covers a range of skill sets, including technical proficiency, critical thinking, and ethical considerations relating to the use of digital tools and platforms (Mokhtari, 2023).

In relation to the variable, Tinmaz et al. (2022) review stresses its key role for students with disabilities in their use of AI tools. In other words, digital literacy (DL) provides students with the required skills to use technology effectively and to easily access and engage with AI-based educational resources compared to traditional materials. Based on the above, personalized learning experiences that meet individual students' needs can be provided. Moreover, DL motivates students with disabilities to engage in their learning environment driven by technology fully, making it more feasible than traditional education, which has several barriers. DL, therefore, promotes the independence and educational outcomes of students with disabilities – an empowerment that is required for their academic success and inclusion in society.

In another related study, Yao and Wang (2024) stress the key role of DL in bringing about positive intention of pre-service special education teachers towards AI adoption in education (AIEd). The authors found DL to be a leading factor in forming the PEU and PU of AIEd among teachers, and in turn, this affected their behavioral intention towards the adoption of AI technologies. In other words, integrating DL into teacher education programs is a must, particularly for special education teachers, for their readiness to adopt AIEd. The authors also found PU to be a top driver of behavioral intention and a mediating factor in the effects of DL. The findings stressed the need to develop training programs that improve teachers' technical proficiency and illustrate AIEd's practical benefits in the special education context.

Students with higher levels of DL are better prepared to interact with AI technologies, which directly influence how easily they perceive such tools. As supported by the TAM framework, external factors like DL are instrumental in shaping PEU, ultimately impacting behavioral intention (Venkatesh & Bala, 2008). Recognizing its practical significance, this study incorporates DL as a foundational element in understanding AI adoption among special needs students.

Thus, this study proposes that DL impacts AI tools' PEU in the following hypothesis:

H3: DL has a positive impact on the PEU of AI technology among special needs students.

Self-efficacy

According to Bandura (1978), self-efficacy (SE) is the belief of the individual that he has the ability to carry out actions required to meet particular goals. In the context of special needs students, the importance of SE lies in its influence over motivation, learning, and achievement in learning (Ziyan & Kadri, 2025). Thus, this covers their confidence in task completion, tackling challenges, and achieving educational objectives in the face of their disabilities. Highly self-efficacious students often persist in task completion, employ learning strategies, and bounce back from any setback, while those who have low SE often steer clear of challenges to avoid the feeling of helplessness (Newberry & Shelton, 2024; Ziyan & Kadri, 2025).

Understanding this variable is crucial in terms of its effect on students' cognitive, social, and identity development. The students' SE can be influenced by instructors through the promotion of a positive learning environment and presenting constructive feedback – all these improve the confidence of students in their abilities and, thus, positively influence their academic process, setting of objectives, and skills in solving problems (Shao et al., 2024; Yao & Wang, 2024).

In the context of TAM, SE is considered vital for PEU because it determines how comfortably users engage with technology (Venkatesh & Bala, 2008). For special needs students, confidence in their ability to use AI tools is critical to overcoming accessibility barriers, justifying its inclusion in this study's model.

Thus, this study proposes the following hypothesis for testing:

H4: SE has a positive impact on PEU of AI technology among special needs students.

Perceived usefulness

The belief of the individual that the system is able to enhance his job performance is PU (Wijayanti et al., 2024). This study defines it as a special needs student's belief that technology has the potential to improve their academic performance and productivity. Meanwhile, PEU is referred to as the level to which the system is perceived as being easy to use, and in the context of special needs students, PEU is the students' perception of the ease with which they can use new technology. The study attempts to examine how external factors of SS, DL, SE, and motivation affect the use of technology among special needs students. In relation to this, intention to use refers to the willingness of the special needs students to use AI technology for their learning objectives and how it meets disability-related needs. The factors influencing the intention to use AI technology are PU, accessibility, and PEU. In

this study, one of the objectives is to test the hypotheses based on the extended TAM from the perspective of special needs students and their use of AI tools.

In past literature, studies like Yao and Wang (2024) and Şahin et al. (2024) found PU to be a positive and significant predictor of continuous intention towards using technology. Specifically, Şahin et al. (2024) studied the influencing factors of intention to use assistive technologies among teachers in inclusive education through the use of extended TAM. Their findings indicated that PU (PU), which is the perception that assistive technologies can enhance the effectiveness of teaching, has a key role in forming the teachers' intention to adopt such technologies. However, it was not the top predictor in their study – the relationship between PU, PEU, and SE stresses its importance in adopting technology. The teachers who perceived the technologies to be useful had a higher likelihood of displaying higher levels of intentions towards using them in inclusive classrooms, which means that such technologies and tools provide practical advantages. The findings support the need for targeted intervention, like real-world illustrations and institutional support, to enhance PU of AI and, in turn, promote its higher acceptance and implementation in inclusive education. In TAM, PU is a key factor directly influencing intention to use, making it essential for understanding AI adoption among special needs students (Davis, 1989). Therefore, PU is proposed to have a higher effect on using technology, and as such, the following hypothesis is proposed:

H5: PU has a significant positive effect on intention to use AI technology.

Perceived ease of use

According to Lutfi et al. (2021), PEU is the level to which the individual is convinced that using a specific system/technology will be effort-free. In the context of special needs students, it is the level to which the student with disabilities is convinced that using a specific technology/system will be intuitive, accessible, and call for the least cognitive, physical, or sensory effort, and takes into account particular needs and abilities (Şahin et al., 2022).

Şahin et al.'s (2024) exploration of the acceptance of assistive technology (AT) by teacher candidates trained in special education and inclusion was conducted using extended TAM. They found PEU to significantly influence PU and behavioral intention (BI), which supports its key role in technology adoption frameworks.

This study's implications highlight the requirement of providing targeted training initiatives for improving the SE and technical proficiency of teacher candidates, after which the perceived barriers to AT use can be minimized. Through PEU, educational institutions can bring about a higher level of acceptance and integration of assistive technologies, eventually culminating in successful inclusive education initiatives. PEU is thus crucial in driving the user's intention towards adopting and using AI technologies. PEU reflects students' belief that they can interact with AI tools without undue effort, which aligns with TAM's emphasis on effort expectancy as a determinant of behavioral intention (Venkatesh & Bala, 2008). For students with disabilities, this construct is vital in evaluating the accessibility and usability of inclusive technologies.

Therefore, this study formulated the following hypothesis:

H6: PEU has a significant positive effect on intention to use AI technology.

METHODOLOGY

RESEARCH DESIGN

The type of approach adopted in this study to achieve the objectives is a mixed method, with which the integration of AI in inclusive education for students with disabilities was explored. This approach is a combination of the quantitative and qualitative approaches, which was suitable to present an in-depth understanding of the topic under study. The study is explanatory and sequential in design, with the quantitative data collection and analysis comprising the first part directed towards determining

patterns and relationships. This is followed by the qualitative data collection and analysis in the second part, directed towards obtaining contextual and experiential aspects of the integration of AI in the learning environment of students with disabilities.

This choice of design also responds to limitations observed in prior research, where many studies on AI adoption in education relied solely on either quantitative or qualitative methods (Lim, 2025; Martín-Núñez et al., 2023). Quantitative studies often lacked contextual depth and overlooked experiential factors critical to students with disabilities, while qualitative studies provided rich insights but did not offer generalizable patterns or statistical validation (Lim, 2025). By adopting a mixed-methods approach, this study addresses these gaps by combining statistical analysis of large-scale data with qualitative exploration of lived experiences, enabling a more holistic and nuanced understanding of AI adoption in inclusive education settings.

INSTRUMENTS

Quantitative instrument

Accordingly, the quantitative phase involved gathering quantitative data using structured surveys distributed to students with disabilities throughout different educational institutions. The surveys focused on obtaining students' perceptions concerning usefulness, ease of use, and barriers to AI adoption, with the measurement items gauged on a 5-point Likert scale. The sources of each construct are shown in Table 1, and the entire survey contents are in the Appendix.

Table 1. The constructs' sources

Construct	Source
Perceived usefulness	(Davis, 1989)
Perceived ease of use	(Davis, 1989)
Intention to use	(Davis, 1989)
Social support	(Collazo-Castiñeira et al., 2022; Zdravkova et al., 2022)
Digital literacy	(Amin et al., 2021)
Self-efficacy	(Wang & Chuang, 2024)
Motivation	(Yurt & Kasarci, 2024)

Qualitative instrument

As for the qualitative part of the study, this entailed the use of semi-structured interviews conducted with eight experts in the AI and inclusive education fields, who were selected on the basis of their experience and expertise in AI tools development and implementation in the context of students with disabilities. The semi-structured interviews were developed to obtain the perspectives of the experts concerning the factors influencing the adoption of AI in inclusive education, covering barriers, enablers, and practical implications of AI. This study used a thematic analysis method to analyze the data obtained, and this enabled the determination of patterns and themes that frequently and repeatedly arose. Added to this, the interviews obtained in-depth insights to complement those of the quantitative ones by highlighting the challenges present in practice, ethical considerations, and effective strategies to integrate AI tools in diverse educational environments. This qualitative part of the study offers a deeper understanding of the distinct drivers of AI adoption and recommendations that practitioners and policymakers can take into consideration.

SAMPLE

With regards to the sample, a purposive sampling strategy was used to ensure that the key stakeholders represent different levels, from educators and administrators among schools with inclusive education, to developers of AI educational tools, and students with disabilities coming from different age groups and from different educational levels. Such an approach ensures that the study manages to

encapsulate a general range of experiences and points of view, supporting the applicability, validity, and relevance of the findings.

Data Collection Procedures

Quantitative data collection

To facilitate recruitment, institutional administrators and disability support coordinators assisted in disseminating the online survey links to eligible students via email and institutional platforms. Data collection for the quantitative phase was carried out over a three-month period from March to May 2024.

Qualitative data collection

Table 2 summarizes the profiles of the eight experts, including their roles, affiliations, and selection criteria. The experts represented diverse academic, technological, and policy backgrounds across Yemen, Saudi Arabia, and Malaysia, ensuring a comprehensive range of perspectives on AI adoption in inclusive education. The interviews were conducted online to accommodate the geographical distribution of participants and were audio-recorded with consent.

Table 2. Experts' profile

Expert No.	Role	Country/ region	Selection criteria
E1	Professor of Educational Technology	Yemen	>15 years in AI & inclusive education research
E2	Associate Professor in Technology Adoption	Saudi Arabia	Experience developing AI tools for students with disabilities
E3	Senior Education Administrator	Yemen	Involvement in inclusive education policy implementation
E4	Associate Professor of Special Education	Saudi Arabia	Expert in social education and AI adoption in inclusive classrooms
E5	Assistant Professor & Lead Data Scientist	Malaysia	Expertise in AI analytics and inclusive learning environments
E6	Senior Lecturer & Research Consultant	Saudi Arabia	Experience in AI applications and educational research
E7	Senior Lecturer in Computer Science & AI	Malaysia	Research in AI systems design and accessibility
E8	Professor of Computer Science	Saudi Arabia	Research on machine learning and accessibility technologies

Data Analysis

Moving on to the data analysis, we began with quantitative data subjected to statistical methods, including descriptive statistics, correlation analysis, and Structural Equation Modeling (SEM), to identify major trends and relationships. On the other hand, thematic analysis was used on qualitative data to determine recurring themes and to obtain insights into the role of AI in inclusive education for students with disabilities. Such dual analysis makes sure that robust findings are presented. Thematic analysis followed a deductive approach, guided by the conceptual framework and research objectives. Two researchers independently reviewed and manually coded the transcripts to identify recurring patterns and categories. Coding discrepancies were resolved through discussion and consensus. This iterative process ensured consistency and strengthened the credibility and trustworthiness of the identified themes.

Ethical Considerations

Prior to the data collection phase, ethical considerations were taken into account, which entailed obtaining ethical approval from the responsible institutions and the study participants. This study received ethical approval from Sunway University Research Ethics Committee (Ref: SUREC 2024/007) on 30 January 2024. The approval covered all study materials, including the ethics application form, consent form, questionnaires, and researcher training compliance (Collaborative Institutional Training Initiative (CITI) certificate). Special consideration was given to the participation of students with disabilities. The online survey platform was designed to be accessible to screen readers and included simple, clear language. Assistance was also made available through institutional disability support services to help participants navigate the survey if needed. Informed consent forms were adapted for accessibility, ensuring all participants could fully understand their rights and voluntarily agree to participate.

The participants were informed about the purpose of the study and their rights in relation to it. They were also assured of confidentiality and their option to drop out of the study at any time they pleased. Their informed consent was obtained in a manner consistent with the principles of ethical research.

Validation of Findings

Another important phase involved the validation of the findings. This was ensured using triangulation and cross-verification of results from both methods to establish both validity and reliability. The survey instrument was pilot tested while the interview sessions were conducted through protocols to ensure that the tools were accurate and the statements were clear. In this methodological framework, actionable insights can be generated concerning the potential of AI integration and the challenges faced by students with disabilities in inclusive education. Overall, this contributes greatly to the development of effective strategies used to improve the learning opportunities, particularly among students with disabilities.

RESULTS

This section presents and discusses the findings obtained from the quantitative and qualitative analyses. The quantitative results cover the relationships between the additional constructs, namely SS, motivation, DL, and SE, and their effect on adopting AI tools in inclusive education. These findings are obtained from the interviews of experts, and they present implications for practice in terms of user-centered design, contextual adaptability, ethical challenges, and professional development. The combined findings provide an in-depth understanding of the factors that influence integrating AI technologies into special needs students' education.

Demographic Findings

The respondents' demographic profile holds information and insight into the sample's characteristics – the sample is generally comprised of students with disabilities in Saudi Arabia. The analysis targets major variables like age, gender, level of education, and type of disability. All the variables illustrate the sample's diversity and their importance to the context of the study. The demographic profiles of the respondents are presented in Table 3.

On the basis of the findings obtained from the demographic profile, there is a balanced representation throughout major variables, presenting insights into the diversified makeup. To begin with, gender distribution is almost balanced, with male respondents making up 52.5% and female respondents making up 47.5%. With regards to their ages, the majority of them were young adults within the age range of 18-34 years (80.5%). This demographic has a higher likelihood of being engaged with emerging technologies, including AI. Moving on to their level of education, it appears that their education is quite diverse, beginning with the majority of them from the bachelor degree programs

(48.3%), PhD programs (17.8%), followed by Master programs (16.9%), and Diploma programs (16.9%). Lastly, based on disability types, physical disabilities lead with 30.5%, followed by hearing impairments at 27.1%, visual impairments at 23.7% and finally, cognitive disabilities at 18.7%. The diverse demographic characteristics stress the need for AI tools to tackle the barriers, challenges, and needs of a broad range of users in inclusive technology.

Table 3. Demographic profile of participants

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	62	52.5%
	Female	56	47.5%
Age group	18–24 years	45	38.1%
	25–34 years	50	42.4%
	35–44 years	23	19.5%
Educational level	Diploma	20	16.9%
	Bachelor	57	48.3%
	Master	20	16.9%
	PhD	21	17.8%
Disability type	Visual impairment	28	23.7%
	Hearing impairment	32	27.1%
	Physical disability	36	30.5%
	Cognitive impairment	22	18.7%

Measurement Model

This section is dedicated to presenting the measurement model's validity and reliability, which was tested through Confirmatory Factor Analysis (CFA) – an analysis that ensures that the observed indicators are accurate in their representation of the latent variables. There are two major aspects focused on, and they are construct validity (convergent and discriminant validity) and reliability. The latter was tested using composite reliability (CR) and Cronbach's alpha coefficient. The study also employed model fit indicators to confirm the measurement model's adequacy, including Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). All these tests establish the robustness of the constructs and make for a strong basis for the evaluation of the structural model. The conceptual model findings obtained from Smart PLS3 are presented in Figure 2.

Measurements of construct validity using confirmatory factor analysis

The study exposed the measurement model to Confirmatory Factor Analysis (CFA) to establish its construct validity and the latent variable's reliability and validity (Hair et al., 2023). Constructs that have construct validity are accurate in their measurement of their corresponding indicators, and these are established using convergent validity and discriminant validity (Hair et al., 2023). The recommended cut-off values for Cronbach's alpha and composite reliability are ≥0.70, indicating acceptable internal consistency (Hair et al., 2023). For average variance extracted (AVE), a value ≥0.50 is considered adequate to establish convergent validity (Hair et al., 2023).

A summarized version of the CFA results with the inclusion of factor loadings, Cronbach's alpha coefficient, CR, and AVE of every construct is presented in Table 4, the values within which confirm their reliability and validity.

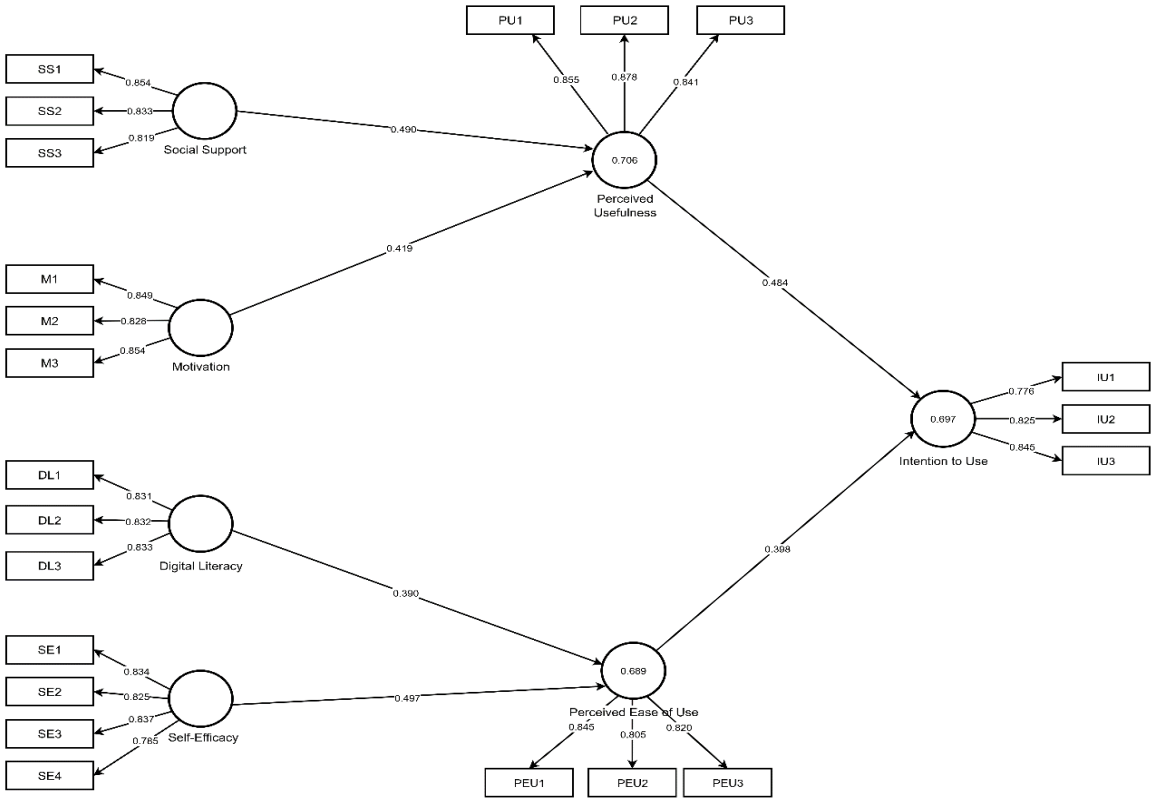

Figure 2. Measurement model

Table 4. Measurements of construct validity

No.	Variable	Code	Factor loading	Cronbach's alpha	Composite reliability (CR)	Ave
1	Perceived Usefulness (PU)	PU1	0.855	0.821	0.893	0.736
		PU2	0.878			
		PU3	0.841			
2	Perceived Ease of Use (PEU)	PEU1	0.845	0.763	0.863	0.678
		PEU2	0.805			
		PEU3	0.820			
3	Intention to Use (IU)	IU1	0.776	0.749	0.857	0.666
		IU2	0.825			
		IU3	0.845			
4	Social Influence (SS)	SS1	0.854	0.783	0.874	0.698
		SS2	0.833			
		SS3	0.819			
5	Digital Literacy (DL)	DL1	0.831	0.777	0.871	0.692
		DL2	0.832			
		DL3	0.833			
6	Self-Efficacy (SE)	SE1	0.834	0.838	0.892	0.673
		SE2	0.925			
		SE3	0.837			
		SE4	0.785			

No.	Variable	Code	Factor loading	Cronbach's alpha	Composite reliability (CR)	Ave
7	Motivation (M)	M1	0.849	0.798	0.881	0.712
		M2	0.828			
		M3	0.854			

HTMT matrix for discriminant validity assessment

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio of Correlations (HTMT), as recommended by Henseler et al. (2015), to determine the extent to which each construct is empirically distinct from the others. The HTMT values for all construct pairs were found to be below the conservative threshold of 0.85, indicating strong evidence of discriminant validity. Specifically, the HTMT values ranged from 0.64 to 0.81. The highest observed value was 0.81 between PU and IU, reflecting a theoretically justified and strong association within technology adoption models, yet still within the acceptable range. Similarly, the HTMT values between PU and PEU (0.78) and between PEU and IU (0.79) also indicated meaningful but distinct relationships.

Constructs that conceptually overlap, such as SE and PEU (0.76), and M and PU (0.75), exhibited moderately high HTMT values, aligning with theoretical expectations while maintaining discriminant validity. The lowest HTMT values were observed between DL and SS (0.64), further confirming the distinctiveness of these latent variables. Overall, the findings substantiate that all constructs are sufficiently discriminant and support the robustness of the measurement model. This is consistent with the established guidelines for evaluating construct validity in partial least squares PLS-SEM as seen in Table 5.

Table 5. Heterotrait-Monotrait (HTMT) ratio matrix for discriminant validity assessment

	PU	PEU	IU	SS	DL	SE	M
PU							
PEU	0.78						
IU	0.81	0.79					
SS	0.73	0.67	0.69				
DL	0.68	0.71	0.66	0.64			
SE	0.70	0.76	0.70	0.66	0.74		
M	0.75	0.68	0.71	0.70	0.65	0.68	

Model fit indicators – Goodness-of-fit (GoF)

The GoF measures are used to evaluate the fit of the proposed model to the observed data, and this is done through the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) – a technique that does not provide traditional model fit indices akin to its counterpart, covariance-based SEM (RMSEA, CFI, and TLI) but rather distinct indicators are utilized for assessing the model fit and quality. Table 6 shows the findings of the model fit.

Table 6. Key model fit indicators

Indicator	Value	Threshold	Interpretation
Standardized Root Mean Square Residual (SRMR)	0.043	≤ 0.08	Indicates an acceptable fit between the predicted and observed correlations.
Normed Fit Index (NFI)	0.924	≥ 0.90	Reflects a good fit of the hypothesized model to the data.

Indicator	Value	Threshold	Interpretation
Chi-Square (χ^2)	432.12	-	Used for reference only; PLS-SEM emphasizes predictive power over absolute fit.
Root Mean Square Residual Covariance (RMS_theta)	0.098	≤ 0.12	Confirms that residual covariances of the outer model meet acceptable thresholds.

Structural Model Analysis

The analysis of the structural model involves testing the hypothesized relationship among the latent variables, the overall predictive strength of the model, and these entail using key metrics, namely path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2).

Hypotheses

The hypothesis testing was done using SEM, as seen in Table 7. The path coefficients are all significant ($p<0.001$), which indicates significant relationships between the constructs. Additionally, Table 8 shows the indirect effects of the independent factors on the intention to use the variable.

Table 7. Path Coefficients

Hypothesis	Path	Coefficient (β)	T-Statistic	P-Value	Decision
H1	SS → PU	0.490	7.476	< 0.001	Supported
H2	M → PU	0.419	5.575	< 0.001	Supported
H3	DL → PEU	0.390	4.319	< 0.001	Supported
H4	SE → PEU	0.497	5.393	< 0.001	Supported
H5	PU → IU	0.484	6.022	< 0.001	Supported
H6	PEU → IU	0.398	4.950	< 0.001	Supported

Table 8. Specific indirect effects

Independent variable	Mediator	Dependent variable	Indirect effect (β)	T-statistic	P-value	Decision
SS	PU	IU	0.237	4.812	< 0.001	Significant
M	PU	IU	0.203	3.788	< 0.001	Significant
DL	PEU	IU	0.155	3.210	< 0.001	Significant
SE	PEU	IU	0.198	3.558	< 0.001	Significant

Coefficient of determination (R^2)

The coefficient of determination (R^2) value represents the proportion of variance that the independent variables explained of their dependent counterpart, as seen in Table 9.

Table 9. R^2 Values

Construct	*R2*	Interpretation
PU	0.706	70.6% of the variance in PU is explained by SS and Motivation.
PEU	0.689	68.9% of the variance in PEU is explained by DL and SE.
IU	0.697	69.7% of the variance in IU is explained by PU and PEU.

Effect size (f^2)

This essentially evaluates the independent variable's contribution to the dependent variable's R^2. Table 10 shows the findings of the effect size. As suggested by Hair et al. (2023), the interpretation of effect size (f^2) in SEM follows established benchmarks: values around 0.02 are considered indicative of a small effect, values near 0.15 represent a medium effect, and those approaching or exceeding 0.35 are indicative of a large effect.

Table 10. f^2 values

Relationship	f^2	Effect size
SS → PU	0.25	Medium
M → PU	0.18	Medium
DL → PU	0.15	Medium
SE → PEU	0.22	Medium
PU → IU	0.38	Large
PEU → IU	0.25	Medium

Based on the results, the model illustrates a combination of small to large effect sizes, with significant contributions of PU to IU.

Predictive Relevance (Q^2)

This key metric determines the predictive relevance of the model through the use of a blindfolding procedure, as seen in Table 11.

Table 11. $Q2$ Values

Construct	Q^2	Interpretation
PU	0.35	PU exhibits strong predictive relevance.
PEU	0.31	PEU exhibits strong predictive relevance.
IU	0.48	IU exhibits strong predictive relevance.

In cases where the predictive relevance (Q^2) values are positive, it is an indication of the model's good predictive relevance.

Qualitative Findings

The qualitative phase of the study consisted of interview sessions conducted with eight field experts in AI for special needs education. Thematic analysis was conducted using a deductive coding approach guided by the conceptual framework. Two researchers independently coded the transcripts, and any discrepancies were resolved through discussion and consensus to ensure consistency and reliability. The interview analysis indicated five main themes (as shown in Table 12) and information on the major factors that influence the adoption of assistive technologies in inclusive education, all of which are explained in the following subsections.

Importance of user-friendly designs

There was unanimous agreement among the experts based on their consistent mention of the prioritization of intuitive and user-friendly designs of assistive technologies to make sure that educators and students can easily access them. On the flip side, complex interfaces or those with overly technical interfaces prevent adoption among teachers, especially those whose DL is limited.

According to experts (E1, E2, E3, E8), "*An intuitive interface is a must to motivate teachers who lack technological know-how to use technology. Complications could prevent using the tool.*" Similarly, experts (E4, E5, E6, E7) stated, "*Customization is necessary because every student has his/her distinct needs, in addition to which, flexible*

technology is more feasible to be adapted to." In other words, simple interfaces that provide customization options can significantly impact users' PEU and PU.

Table 12. Summary of themes from thematic analysis

Theme no.	Theme title	Description
1	Importance of User-Friendly Designs	Highlights the need for intuitive, accessible interfaces and customization options in AI tools.
2	Contextual Adaptability	Emphasizes adapting AI technologies to local cultural, linguistic, and educational contexts.
3	Ethical Considerations and Privacy	Addresses concerns about data privacy, algorithmic bias, and the ethical design of AI systems.
4	Potential for Fostering Autonomy	Explores AI's role in supporting student independence while maintaining teacher-student interaction.
5	Professional Development and Collaboration	Stresses the need for ongoing training and collaboration between educators and developers.

Contextual adaptability

The contextual adaptability of assistive technologies to particular contexts, whether cultural, linguistic, or educational, was highlighted as the top driver of implementation success. According to the experts, ineffective generic solutions in diverse settings could only lead to failure – based on experts (E4, E6), "*The technology needs to be consistent with the local cultural and linguistic contexts. A case in point is it needs to support multiple languages for diverse classrooms,*" while experts (E5, E7, E8) added, "*A generic approach will fail, and as such, developers need to consider the specific needs of various schools in different regions.*" This feedback emphasizes the importance of creating technologies that meet the needs of every user, contributing to the technological effectiveness and relevance in the context of an inclusive learning environment.

Ethical considerations and privacy

Data privacy and algorithmic bias are touched upon as ethical issues that were related to the experts' concerns, with all experts (E1-E8) stating that, "*There is a need to ensure the students' data security, as without privacy measures, the students' trust in the tools will eventually erode.*" Moreover, another expert stressed, "*Bias in algorithms is a top concern because without careful consideration of the AI design, it could have detrimental effects on the targeted students.*" All these concerns emphasize the need for transparency, AI ethical design, and robust data protection through policies that capture and assuage trust and equitable results.

Potential for fostering autonomy

The potential of AI to motivate students with special needs to be independent and autonomous in their learning was noted by the experts. According to experts (E2, E3, E6, E7), "*AI motivates students to take control over their learning as, through its personalized feedback and adaptive tools, the students can develop their learning independence.*" Nevertheless, the experts also cautioned against the over-dependence on human connection in education, which would go against the irreplaceable role of teachers. These insights from the experts reveal that assistive technologies need to improve instead of replace human interaction while promoting collaboration and independence of students.

Professional development and collaboration

A significant barrier to adopting AI tools and technology is the lack of continuous professional development of instructors and educators. According to the experts, comprehensive training initiatives need to be provided so that teachers will have the skills to effectively integrate assistive technologies in the learning environment. Some experts (E1, E4, E5, E8) stated, "*There is a need for continuous training for the complete leveraging of the tools, and thus, a single workshop is not sufficient for successful integration.*" Another one revealed that developers-educators' collaboration is a must for aligning technology with

classroom needs. All these findings stress the requirement for training and collaboration to minimize the gap between technological capabilities and classroom practice.

DISCUSSION

Critical factors that influence the adoption of AI tools among students with disabilities are the focus of this study, which aims to provide insights into inclusive education. The study examines the roles of SS, motivation, DL, and SE, the findings of which showed consistency with prior studies, e.g., Marino et al. (2023) and Ramaiah et al. (2025). The study suggests that systematic efforts need to be made to address the technical and social barriers to AI technology adoption and pave the way for inclusive and effective educational technologies and learning/teaching practices.

The study adopted extended TAM as the underpinning theory, which explains the factors' roles and compares them with past relevant studies to present implications for inclusive education practice.

On the basis of this study's findings, SS has an indirect significant effect on the perceptions of students with disabilities over the usefulness of AI tools. This is similar to the reported findings of Guo (2024) and Hong and Kim (2024), who found social networks (educators, peers, and family) to have a key contribution to promoting positive attitudes towards using technology.

In a study of the same caliber, Marino et al. (2023) revealed the need for collaboration of educators and parents in the use of AI tools among students with disabilities, contending that a supportive learning environment could culminate in improved perceived benefits of the AI tools and ultimately higher adoption levels. Also, Opoku et al. (2023) found that training and encouragement from teachers have a significant role in enhancing PU of assistive technologies among special needs students. The findings support the premise that support brings about AI integration success in inclusive education. Thus, schools need to practically promote stakeholders' collaboration for a supportive ecosystem that motivates AI adoption – case in point, peer mentoring initiatives and educators' workshops can make for a strong social fabric that is required for technology adoption sustainability.

Added to the above, motivation was found to be a top determinant of PU as students who are motivated towards overcoming academic challenges and enhancing their learning experiences are more willing to perceive the benefits of AI tools. This finding is supported by the findings reported by past studies that indicated intrinsic motivation to have a positive role in adopting educational technologies among students with disabilities, i.e., Habib and Janae (2024) and Patibandla et al. (2024).

Notably, the motivation-PU relationship has also been investigated in gamified learning environments, where it was revealed that rewards and challenges, both gamification elements, were able to increase the intrinsic motivation of students (Kashive & Mohite, 2023), contributing to their perceptions of the value of technology. The study presented a comparable role of motivation by emphasizing the potential of the gamified features of the AI tools to motivate engagement among students with disabilities. In future studies, integrating motivational strategies can be a topic worth examining, and these include goal-setting and progress tracking for enhanced perceived value and sustained usage of AI tools.

Moreover, a factor that was found to have a significant influence over PEU is DL, indicating that students who are good at using digital tools have a higher likelihood of perceiving them as user-friendly, which affects their intention towards their use. This aligns with the findings from Tinmaz et al. (2022), who revealed that DL training is a must for students with disabilities to minimize the barriers towards technology adoption. Also, past studies found that students equipped with higher DL levels had more confidence in their use as well as higher engagement levels (Yao & Wang, 2024). These findings align with the present study, which emphasizes the role that DL has in facilitating inclusive education. In this regard, institutions need to provide training programs for both students and educators – those that target developing basic skills and offering hands-on experience in the handling of assistive technologies.

Added to the above findings, SE was revealed to be the top predictor of PEU, as evidenced by the ability of confident students to use AI tools and their role in forming their use perceptions and intention to adopt. Yao and Wang's (2024) findings were consistent with this finding, as they found SE to have a significant role in the inclination towards new technology engagement among students. Therefore, SE needs to be promoted through practical strategies such as the provision of incremental learning opportunities and real-time feedback within the AI platforms, and in so doing, students can increasingly gain confidence and proficiency.

The study found both PU and PEU to have a significant influence on intention towards AI tools usage, validating the core premise of TAM as developed by Davis (1989) and aligning with recent educational technology studies. This is evidenced by Şahin and Yıldız's (2024) study, which reported PU to be the top significant driver of technology adoption among students with disabilities, directly relating to their performance in academia. Similar to this study, the importance of designing user-friendly and directly beneficial AI tools for students' academic objectives is highlighted. Also, there is a need for developers to have intuitive interfaces and functionalities as their top priority in order to meet the learning challenges of students with disabilities head-on.

In addition to the quantitative results, the qualitative findings highlight the multiple challenges and opportunities relating to assistive technologies adoption in inclusive education and the critical requirement for user-centered design, contextual adaptability, ethical considerations, student autonomy support, and educators' continuous professional development. Such insights go hand in hand with the quantitative findings as they enrich the understanding of the practical and contextual factors influencing the adoption and implementation of AI assistive technologies.

The qualitative insights emphasized that user-friendly and intuitive interfaces are essential for promoting adoption among educators and students, especially those with lower levels of DL. This finding aligns with Mukred et al. (2023), who highlighted PEU as a critical determinant in technology acceptance. Complex or technical designs act as barriers, reinforcing the need for developers to integrate customization options and accessibility features to accommodate diverse needs (Yao & Wang, 2024). User-centered design principles, therefore, remain vital in ensuring the successful implementation of AI tools in inclusive education settings.

Experts underscored the need for AI tools to be adaptable to specific cultural, linguistic, and educational contexts. This reflects the work of Bitar and Davidovitch (2024), who argued that educational technologies not tailored to local settings often fail to deliver meaningful impact. A generic approach can exacerbate inequities, whereas context-sensitive solutions can promote engagement and inclusivity. Future interventions must consider regional diversity and prioritize localized content to optimize AI tool effectiveness in varied classroom environments.

Concerns about data privacy and algorithmic bias raised by experts echo the work of Mukred et al. (2023), who warned of the ethical challenges in deploying AI in education. For students with disabilities, these issues are particularly critical due to the sensitivity of their personal data. Trust in AI tools is vital and depends on robust privacy safeguards (Anderson et al., 2025), transparent algorithms, and policies ensuring equitable outcomes. Institutions and developers should collaborate to embed ethical principles throughout the AI lifecycle to avoid reinforcing existing biases or compromising student safety.

The potential of AI to support student independence aligns with Al-Motrif (2025), who found that adaptive technologies promote self-directed learning. Personalized feedback mechanisms and adaptive pathways empower students to manage their learning effectively. However, caution is needed to avoid over-reliance on AI at the expense of teacher-student relationships. Balanced integration of AI and human interaction will be critical in supporting both autonomy and social-emotional development.

The lack of ongoing professional development for educators was identified as a barrier to AI adoption (Rajput, 2025). Sustained teacher training is a cornerstone for successful technology integration. One-off workshops are insufficient; continuous learning opportunities and collaborative efforts between developers and educators are needed to align AI tools with real classroom challenges. Building such ecosystems of support will enhance teachers' confidence and competence in using AI for inclusive education.

CONCLUSION

This study identifies key drivers of AI tool adoption among students with disabilities, offering essential insights for inclusive education. It emphasizes the roles of SS, motivation, DL, and SE, highlighting the need for targeted efforts to overcome technical and social barriers and promote more inclusive educational practices.

CONTRIBUTIONS

This study has several significant contributions to theory and practice, which are enumerated in the next subsections.

Implications for theory

This study contributes to theory through the extended TAM, the additional factors of which are SS, M, DL, and SE. These were examined for their influence on the adoption of assistive technologies in inclusive education. The research is enriched through the inclusion of these factors as they shed light on how individual and contextual factors form the students' perceptions regarding PU and PEU and the effects of both the latter on the intention to use assistive technology (IUC). The findings supported the mediating PU and PEU roles and the indirect influence of social and individual factors on IUC through them. In particular, SS and motivation had significant effects on PU, indicating how important emotional and practical encouragement is in forming perceptions towards using technology. This aligns with recent work by Yurt and Kasarci (2024), who found that intrinsic motivation and peer support are significant predictors of AI tool adoption in educational contexts.

DL and SE also had significant effects on PEU, indicating that skills and confidence are required to minimize perceived effort in using technology. Recent findings by Yao and Wang (2024) further support this, demonstrating that digital competence and SE are crucial to PEU in AI-enhanced inclusive classrooms. Through the validation of the proposed extended TAM framework, the study manages to bridge the literature gaps as it explores the interrelationships between social, individual, and technological factors, specifically in inclusive education for students with disabilities. This approach echoes the recommendations of Şahin et al. (2024), who emphasize the value of extending TAM with social and pedagogical factors in special education settings. The study proposed an extended TAM for special education as a robust foundation that sheds light on the effective integration of assistive technologies into real-life educational practices, providing insights for future studies dedicated to the acceptance of technology in the field of education.

Implications for practice and policy

The significant contributions of this study to practice lie in its provision of actionable insights for the adoption of enhanced assistive technologies, particularly in inclusive education among students with disabilities. The findings lay emphasis on the need to keep individual and institutional factors into consideration for the promotion of technology adoption and integration. The investigation into SS, motivation, DL, and SE in light of their effects highlights the need to develop targeted interventions like comprehensive training programs, initiatives for peer mentoring, and support networks for direct stakeholders. This aligns with recent findings by Navas-Bonilla et al. (2025), who emphasize the importance of personalized digital tools and collaborative learning environments in fostering inclusive education practices.

Additionally, the model, as validated by the findings, provides a roadmap on which policymakers and educational institutions can build design strategies for enhanced teacher preparedness. This is best exemplified by the integration of hands-on workshops and the adoption of actual assistive technologies into teacher education initiatives that can promote enhanced PEU and PU. A recent study by Sulaimani and Bagadood (2023) underscores the necessity of targeted funding and specialized teacher training to effectively integrate technology in inclusive education settings. Also, the development of a supportive environment using collaborative platforms, technical assistance, and continuous professional development can bring about a higher adoption rate. The alignment of the required strategies with distinct teacher needs can lead to practical guidelines to enhance inclusive education practices and to ensure the leveraging of assistive technology by special needs students. Furthermore, a systematic review by Navas-Bonilla et al. (2025) highlights that educational technologies transform learning environments into more inclusive and accessible spaces by adapting to the diverse needs of students, facilitating personalized and equitable learning.

Future Work

The study findings and contributions were the basis for the recommendations that this study enumerates for future investigation avenues in the hopes of advancing the understanding of assistive technologies implementation in inclusive education. The first recommendation is the future adoption of longitudinal studies to examine the perceptions of students with disabilities concerning the use of assistive technologies over time in inclusive education. Research along this line could provide insights into the way practical experiences and institutional support affect the long-term adoption and use of the sustainability of AI-driven technologies.

The second recommendation pertains to future studies examining other external factors like cultural differences, resource availability, and policy frameworks that have a hand in adopting assistive technologies. Such an examination could furnish an enriching, holistic explanation of the factors that drive and prevent technology implementation and adoption in various educational contexts, even in environments with a lack of resources.

The third recommendation relates to the future studies' testing of the effectiveness of different training initiatives to promote and improve DL, SE, and motivation among students with disabilities. In relation to this, the comparison among pedagogical approaches like gamification, virtual simulations, and collaborative learning could unearth the top-promoting methods of adoption and proficiency of assistive technologies usage.

Study Limitations

This study has several limitations that should be taken into account when interpreting the findings. The quantitative phase was conducted among students with disabilities from selected educational institutions in Saudi Arabia. While this provided valuable insights into the local context, it may limit the generalizability of the results to other countries or academic systems. The qualitative phase involved only eight expert participants, which, although sufficient for in-depth exploration, may not capture the full diversity of perspectives in the field of AI and inclusive education. Additionally, the cross-sectional design restricts the ability to draw causal inferences about the relationships between variables. The reliance on self-reported data may also introduce biases such as social desirability or recall inaccuracies. Future research could address these limitations by employing longitudinal designs, expanding sample diversity, and incorporating observational or experimental methods to validate and extend these findings.

References

Abu Mukh, Y. N., Abd-Rabo, A. M., & Tarteer, S. (2024). Computer competencies needed for implementing artificial intelligence in special education schools from the perspective of pre-service teachers. *Trends in Higher Education, 3*(3), 602-622. https://doi.org/10.3390/higheredu3030035

Ali, M. (2024). AI and intelligent tutoring systems: A new paradigm for student-centered learning. *Journal of Artificial Intelligence Integration in Education and Machine Learning, 1*(2), 1-11.

Al-kfairy, M., Ahmed, S., & Khalil, A. (2024). Factors impacting users' willingness to adopt and utilize the metaverse in education: A systematic review. *Computers in Human Behavior Reports*, 100459. https://doi.org/10.1016/j.chbr.2024.100459

Almalky, H. A., & Alwahbi, A. A. (2023). Teachers' perceptions of their experience with inclusive education practices in Saudi Arabia. *Research in developmental disabilities, 140*, 104584. https://doi.org/10.1016/j.ridd.2023.104584

Al-Motrif, A. (2025). Enhancing learning experiences for students with learning disabilities through digital pedagogies: Insights from Saudi schools. *Interactive Learning Environments*, *33*(5), 3635-3662. https://doi.org/10.1080/10494820.2024.2446539

Almufareh, M. F., Kausar, S., Humayun, M., & Tehsin, S. (2024). A conceptual model for inclusive technology: Advancing disability inclusion through artificial intelligence. *Journal of Disability Research, 3*(1), 20230060. https://doi.org/10.57197/JDR-2023-0060

Almuhanna, M. A. (2025). Teachers' perspectives of integrating AI-powered technologies in K-12 education for creating customized learning materials and resources. *Education and Information Technologies*, 30, 10343-10371. https://doi.org/10.1007/s10639-024-13257-y

Almurayziq, T. S., Alshammari, G. K., Alshammari, A., Alsaffar, M., & Aljaloud, S. (2022). Evaluating AI techniques for blind students using voice-activated personal assistants. *International Journal of Computer Science and Network Security, 22*(1), 61-68. https://doi.org/10.22937/IJCSNS.2022.22.1.10

Alnahdi, G. (2020). Are we ready for inclusion? Teachers' perceived self-efficacy for inclusive education in Saudi Arabia. *International Journal of Disability, Development and Education, 67*(2), 182-193. https://doi.org/10.1080/1034912X.2019.1634795

Alqahtani, S., Cooper, R., & Cooper, R. A. (2023). Current state and conceptual framework of assistive technology provision in Saudi Arabia. *Disability and Rehabilitation: Assistive Technology, 18*(8), 1357-1363. https://doi.org/10.1080/17483107.2021.2008027

Alsolami, A. (2024). The educational journey of students with disabilities in Saudi Arabia: From isolation to inclusive education. *Remedial and Special Education, 45*(6), 359-368. https://doi.org/10.1177/07419325241240058

Alsolami, A. S. (2025). The effectiveness of using artificial intelligence in improving academic skills of school-aged students with mild intellectual disabilities in Saudi Arabia. *Research in Developmental Disabilities, 156*, 104884. https://doi.org/10.1016/j.ridd.2024.104884

Alzahrani, M. A. (2025). The importance of assistive technology for students with disabilities in the comprehensive education schools in the KSA. *Creative Education, 16*(4), 453-476. https://doi.org/10.4236/ce.2025.164028

Amin, H., Malik, M. A., & Akkaya, B. (2021). Development and validation of digital literacy scale (DLS) and its implication for higher education. *International Journal of Distance Education and E-Learning, 7*(1), 24-43. https://doi.org/10.36261/ijdeel.v7i1.2224

Anderson, R., Cowart, S., Lippincott, B., & Morris, J. (2025). Artificial intelligence and disabled adults: Current use, perceptions, and future development. *Archives of Physical Medicine and Rehabilitation, 106*(4), e140. https://doi.org/10.1016/j.apmr.2025.01.363

Bandura, A. (1978). Self-efficacy: Toward a unifying theory of behavioral change. *Advances in Behaviour Research and Therapy, 1*(4), 139-161. https://doi.org/10.1016/0146-6402(78)90002-4

Bitar, N., & Davidovitch, N. (2024). Cultural adaptation of digital learning tools in Israeli higher education: A case study of lecturer perceptions and practices. *TechTrends, 68*(6), 1152-1165. https://doi.org/10.1007/s11528-024-01007-3

Bressane, A., Zwirn, D., Essiptchouk, A., Saraiva, A. C. V., de Campos Carvalho, F. L., Formiga, J. K. S., de Castro Medeiros, L. C., & Negri, R. G. (2024). Understanding the role of study strategies and learning disabilities on student academic performance to enhance educational approaches: A proposal using artificial intelligence. *Computers and Education: Artificial Intelligence, 6*, 100196. https://doi.org/10.1016/j.caeai.2023.100196

Chalkiadakis, A., Seremetaki, A., Kanellou, A., Kallishi, M., Morfopoulou, A., Moraitaki, M., & Mastrokoukou, S. (2024). Impact of artificial intelligence and virtual reality on educational inclusion: A systematic review of technologies supporting students with disabilities. *Education Sciences, 14*(11), 1223. https://doi.org/10.3390/educsci14111223

Chiu, M.-C., Hwang, G.-J., Hsia, L.-H., & Shyu, F.-M. (2024). Artificial intelligence-supported art education: A deep learning-based system for promoting university students' artwork appreciation and painting outcomes. *Interactive Learning Environments, 32*(3), 824-842. https://doi.org/10.1080/10494820.2022.2100426

Collazo-Castiñeira, P., Rodríguez-Rey, R., Garrido-Hernansaiz, H., & Collado, S. (2022). Prediction of post-traumatic growth in the face of the COVID-19 crisis based on resilience, post-traumatic stress and social participation: A longitudinal study. *Frontiers in Psychology, 13*, 985879. https://doi.org/10.3389/fpsyg.2022.985879

Coy, A., Mohammed, P. S., & Skerrit, P. (2025). Inclusive deaf education enabled by artificial intelligence: The path to a solution. *International Journal of Artificial Intelligence in Education*, *35*, 96-134. https://doi.org/10.1007/s40593-024-00419-9

Darwish, D. (Ed.). (2025). *Artificial intelligence implementation in education processes*. Deep Science Publishing. https://doi.org/10.70593/978-81-984306-7-0

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

Elshazly, E. (2025). Promoting accessibility and personalizing learning experiences through AI. In A. Walters (Ed.), *Transforming special education through artificial intelligence* (pp. 139-164). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-5538-1.ch005

Eziamaka, N., Odonkor, T., & Akinsulire, A. (2024). AI-driven accessibility: Transformative software solutions for empowering individuals with disabilities. *International Journal of Applied Research in Social Sciences, 6*(8), 1612-1641. https://doi.org/10.51594/ijarss.v6i8.1373

Grant, M. C. (2018). IDEA and inclusive education: Issues, implications, and practices. In P. Epler (Ed.), *Instructional strategies in general education and putting the Individuals with Disabilities Act (IDEA) into practice* (pp. 1-38). IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-5225-3111-1.ch001

Guo, Y. (2024). Examining the impact of assistive technology on psychological health, family education, and curriculum research in Japan: Insights from artificial intelligence. *Journal of Autism and Developmental Disorders, 54*(10), 3823-3836. https://doi.org/10.1007/s10803-023-06105-4

Habib, H., & Janae, J. (2024). Breaking barriers: How AI is transforming special education classrooms. *Bulletin of Engineering Science and Technology, 1*(2), 86-108.

Hair, J. F., Jr., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2023). *Advanced issues in partial least squares structural equation modeling* (2nd ed.). Sage. https://doi.org/10.1007/978-3-319-05542-8_15-3

Heeg, D. M., & Avraamidou, L. (2025). Young children's understanding of AI. *Education and Information Technologies*, *30*, 10207-10230. https://doi.org/10.1007/s10639-024-13169-x

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*, 115-135. https://doi.org/10.1007/s11747-014-0403-8

Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., Santos, O. C., Rodrigo, M. T., Cukurova, M., Bittencourt, I. I., & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education*, *32*, 504-526. https://doi.org/10.1007/s40593-021-00239-1

Hong, H., & Kim, Y. (2024). Applying artificial intelligence in career education for students with intellectual disabilities: The effects on career self-efficacy and learning flow. *Education and Information Technologies*, *29*, 25237–25256. https://doi.org/10.1007/s10639-024-12809-6

Jabali, O., & Ayyoub, A. (2024). Smart parenting: Effortless routine engagement with AI support: A quantitative study. *Education and Information Technologies*, *29*, 25403-25425. https://doi.org/10.1007/s10639-024-12854-1

Kashive, N., & Mohite, S. (2023). Use of gamification to enhance e-learning experience. *Interactive Technology and Smart Education, 20*(4), 554-575. https://doi.org/10.1108/ITSE-05-2022-0058

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y.-S., Kay, J., Knight, S., Martinez-Maldonado, R., Shazia Sadiq, S., & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3*, 100074. https://doi.org/10.1016/j.caeai.2022.100074

Kumari, R. K. (2025). Artificial intelligence in special education: Enhancing learning outcomes for students with disabilities. In A. Walters (Ed.), *Transforming special education through artificial intelligence* (pp. 79-112). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-5538-1.ch003

Lai, C. Y., Cheung, K. Y., & Chan, C. S. (2023). Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: An extension of the technology acceptance model. *Computers and Education: Artificial Intelligence, 5*, 100178. https://doi.org/10.1016/j.caeai.2023.100178

Lee, A. T., Ramasamy, R. K., & Subbarao, A. (2025). Understanding psychosocial barriers to healthcare technology adoption: A review of TAM Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology and UTAUT Frameworks. *Healthcare, 13*(3), 250. https://doi.org/10.3390/healthcare13030250

Li, L., & Ruppar, A. (2021). Conceptualizing teacher agency for inclusive education: A systematic and international review. *Teacher Education and Special Education, 44*(1), 42-59. https://doi.org/10.1177/0888406420926976

Lim, W. M. (2025). What is qualitative research? An overview and guidelines. *Australasian Marketing Journal, 33*(2), 199-229. https://doi.org/10.1177/14413582241264619

Lin, H., & Chen, Q. (2024). Artificial intelligence (AI)-integrated educational applications and college students' creativity and academic emotions: students and teachers' perceptions and attitudes. *BMC Psychology, 12*, Article 487. https://doi.org/10.1186/s40359-024-01979-0

Lutfi, A., Al-Okaily, M., Alshirah, M. H., Alshira'h, A. F., Abutaber, T. A., & Almarashdah, M. A. (2021). Digital financial inclusion sustainability in Jordanian context. *Sustainability, 13*(11), 6312. https://doi.org/10.3390/su13116312

Marino, M. T., Vasquez, E., Dieker, L., Basham, J., & Blackorby, J. (2023). The future of artificial intelligence in special education technology. *Journal of Special Education Technology, 38*(3), 404-416. https://doi.org/10.1177/01626434231165977

Martín-Núñez, J. L., Ar, A. Y., Fernández, R. P., Abbas, A., & Radovanović, D. (2023). Does intrinsic motivation mediate perceived artificial intelligence (AI) learning and computational thinking of students during the COVID-19 pandemic? *Computers and Education: Artificial Intelligence, 4*, 100128. https://doi.org/10.1016/j.caeai.2023.100128

Mishra, P. (2025). Revolutionizing education with AI and ML. In M. Ouaissa, M. Ouaissa, H. Lamaazi, M. El Hamlaoui, & K. Reddy C. (Eds.), *Internet of behavior-based computational intelligence for smart education systems* (pp. 53-94). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-8151-9.ch003

Mokhtari, F. (2023). Fostering digital literacy in higher education: Benefits, challenges and implications. *International Journal of Linguistics, Literature and Translation, 6*(10), 160-167. https://doi.org/10.32996/ijllt

Mukred, M., Asma, M. U., & Hawash, B. (2023). Exploring the acceptance of ChatGPT as a learning tool among academicians: A qualitative study. *Jurnal Komunikasi: Malaysian Journal of Communication, 39*(4), 306-323. https://doi.org/10.17576/JKMJC-2023-3904-16

Navas-Bonilla, C. D. R., Guerra-Arango, J. A., Oviedo-Guado, D. A., & Murillo-Noriega, D. E. (2025). Inclusive education through technology: A systematic review of types, tools and characteristics. *Frontiers in Education, 10*, 1527851. https://doi.org/10.3389/feduc.2025.1527851

Neeharika, C. H., & Riyazuddin, Y. M. (2023, January). Artificial intelligence in children with special need education. *Proceedings of the International Conference on Intelligent Data Communication Technologies and Internet of Things*; *Bengaluru, India,* 519-523. https://doi.org/10.1109/IDCIoT56793.2023.10053420

Newberry, C. M., & Shelton, R. N. (2024). Remote learning and equitable services: A review of the impact of COVID-19 school closures on special education students and teachers. In P. M. Davies (Ed.), *Global perspectives on online education during a time of emergency: Conditions, contexts and critiques* (pp. 161-173). Vernon Press.

Opoku, M. P., Elhoweris, H., Alhosani, N., Mustafa, A., Alkhateri, T., & Nketsia, W. (2023). Factors influencing the intention of trainee special education teachers to integrate assistive technology into teaching students with disabilities in the United Arab Emirates. *Heliyon, 9*(12), e22736. https://doi.org/10.1016/j.heliyon.2023.e22736

Oyedokun, T. T. (2025). Assistive technology and accessibility tools in enhancing adaptive education. In E. Çela, M. Fonkam, N. Vajjhala, & P. Eappen (Eds.), *Advancing adaptive education: Technological innovations for disability support* (pp. 125-162). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-8227-1.ch006

Patel, N. S., & Indurkhya, N. (Eds.). (2025). *The rise of intelligent machines: A multi-disciplinary perspective from industry and impact on higher education.* Chapman and Hall/CRC Press. https://doi.org/10.1201/9781003469551

Patibandla, R. L., Rao, B. T., Rao, D. M., & Ramakrishna Murthy, M. (2024). Reshaping the future of learning disabilities in higher education with AI. In R. Kaluri, M. Mahmud, T. R. Gadekallu, D. S. Rajput, & K. Lakshmanna (Eds.), *Applied assistive technologies and informatics for students with disabilities* (pp. 17-33). Springer. https://doi.org/10.1007/978-981-97-0914-4_2

Pierrès, O., Christen, M., Schmitt-Koopmann, F. M., & Darvishy, A. (2024). Could the use of AI in higher education hinder students with disabilities? A scoping review. *IEEE Access, 12*, 27810-27828. https://doi.org/10.1109/ACCESS.2024.3365368

Rajput, R. (2025). Overcoming barriers to AI implementation in the classroom: A roadmap for educational transformation. In U. Sarwar, T. Sanhong, M. Waheed Akhtar, & M. Aamir (Eds.), *Navigating barriers to AI implementation in the classroom* (pp. 401-436). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3373-1827-1.ch015

Ramaiah, M. S., Nagarajan, S. K. S., Whig, P., & Dutta, P. K. (2025). AI-powered innovations transforming adaptive education for disability support. In E. Çela, M. Fonkam, N. Vajjhala, & P. Eappen (Eds.), *Advancing adaptive education: Technological innovations for disability support* (pp. 73-100). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-8227-1.ch004

Rice, M. F., & Dunn, S. (2023). The use of artificial intelligence with students with identified disabilities: A systematic review with critique. *Computers in the Schools, 40*(4), 370-390. https://doi.org/10.1080/07380569.2023.2244935

Roberts, B. (2022). *"The last great inclusion": A look at education reform policy through a disability studies lens* [Bachelor dissertation, Wesleyan University].

Şahin, F., Doğan, E., Yıldız, G., & Okur, M. R. (2022). University students with special needs: Investigating factors influencing e-learning adoption. *Australasian Journal of Educational Technology, 38*(5), 146-162. https://doi.org/10.14742/ajet.7454

Şahin, F., Kızılaslan, A., & Şimşek, Ö. (2024). Factors influencing the acceptance of assistive technology by teacher candidates in the context of inclusive education and special needs students. *Education and Information Technologies, 29*(10), 12263-12288. https://doi.org/10.1007/s10639-023-12383-3

Şahin, F., & Yıldız, G. (2024). Understanding mobile learning acceptance among university students with special needs: An exploration through the lens of self-determination theory. *Journal of Computer Assisted Learning, 40*(4), 1838-1851. https://doi.org/10.1111/jcal.12986

Salhab, R. A. (2025). Inclusive education in the artificial intelligence era: Opportunities and challenges. In M. Sanmugam, B. Edwards, N. Mohd Barkhaya, & Z. Khlaif (Eds.), *Fostering inclusive education with AI and emerging technologies* (pp. 1-24). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-7255-5.ch001

Scott, L. M., Wilder, T., Zaugg, T., & Romualdo, A. (2025). Enhancing special education using AI: The intersection of personalized learning and inclusivity. In A. Walters (Ed.), *Transforming special education through artificial intelligence* (pp. 45-78). IGI Global. https://doi.org/10.4018/979-8-3693-5538-1.ch002

Sethi, S. S., & Jain, K. (2024). AI technologies for social emotional learning: Recent research and future directions. *Journal of Research in Innovative Teaching & Learning, 17*(2). 213-225. https://doi.org/10.1108/JRIT-03-2024-0073

Shao, C., Nah, S., Makady, H., & McNealy, J. (2024). Understanding user attitudes towards AI-enabled technologies: An integrated model of self-efficacy, TAM, and AI ethics. *International Journal of Human-Computer Interaction*, *41*(5), 3053-3065. https://doi.org/10.1080/10447318.2024.2331858

Sulaimani, M. F., & Bagadood, N. H. (2023). Assistive technology for students with intellectual disability: Examining special education teachers 'perceptions in Saudi Arabia. *Assistive Technology, 35*(3), 235-241. https://doi.org/10.1080/10400435.2022.2035017

Tinmaz, H., Lee, Y.-T., Fanea-Ivanovici, M., & Baber, H. (2022). A systematic review on digital literacy. *Smart Learning Environments, 9*, Article 21. https://doi.org/10.1186/s40561-022-00204-y

Torres, E. R., Rodríguez, R. C., & Briñez, E. T. (2023). Use of AI to improve the teaching-learning process in children with special abilities. *LatIA, (1)*21. https://doi.org/10.62486/latia202321

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Wang, Y.-Y., & Chuang, Y.-W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies, 29*(4), 4785-4808. https://doi.org/10.1007/s10639-023-12015-w

Wijayanti, P., Mohamed, I. S., & Daud, D. (2024). Computerized accounting information systems: An application of task technology fit model for microfinance. *International Journal of Information Management Data Insights, 4*(1), 100224. https://doi.org/10.1016/j.jjimei.2024.100224

Yao, N., & Wang, Q. (2024). Factors influencing pre-service special education teachers' intention toward AI in education: Digital literacy, teacher self-efficacy, perceived ease of use, and perceived usefulness. *Heliyon, 10*(14), e34894. https://doi.org/10.1016/j.heliyon.2024.e34894

Yin, J., Goh, T.-T., & Hu, Y. (2024). Interactions with educational chatbots: The impact of induced emotions and students' learning motivation. *International Journal of Educational Technology in Higher Education, 21*, Article 47. https://doi.org/10.1186/s41239-024-00480-3

Yurt, E., & Kasarci, I. (2024). A Questionnaire of Artificial Intelligence Use Motives: A contribution to investigating the connection between AI and motivation. *International Journal of Technology in Education, 7*(2), 308-325. https://doi.org/10.46328/ijte.725

ZainEldin, H., Gamel, S. A., Talaat, F. M., Aljohani, M., Baghdadi, N. A., Malki, A., Badawy, M., & Elhosseini, M. A. (2024). Silent no more: A comprehensive review of artificial intelligence, deep learning, and machine learning in facilitating deaf and mute communication. *Artificial Intelligence Review, 57*, Article 188. https://doi.org/10.1007/s10462-024-10816-0

Zaugg, T. (2025). Future innovations for assistive technology and universal design for learning. In K. K. Floyd, T. Jeffs & K. S. Puckett (Eds.), *Assistive technology and universal design for learning: Toolkits for inclusive instruction* (pp. 275-318). Plural Publishing.

Zdravkova, K., Krasniqi, V., Dalipi, F., & Ferati, M. (2022). Cutting-edge communication and learning assistive technologies for disabled children: An artificial intelligence perspective. *Frontiers in Artificial Intelligence, 5*, 970430. https://doi.org/10.3389/frai.2022.970430

Zhang, J., & Zhang, Z. (2024). AI in teacher education: Unlocking new dimensions in teaching support, inclusive learning, and digital literacy. *Journal of Computer Assisted Learning, 40*(4), 1871-1885. https://doi.org/10.1111/jcal.12988

Zhang, L., Carter, R. A., Liu, Y., & Peng, P. (2024). Let's CHAT about artificial intelligence for students with disabilities: A systematic literature review and meta-analysis. *Review of Educational Research*. https://doi.org/10.3102/00346543241293424

Zhou, T. (2017). The effect of social support on post-adoption of mobile SNS. *International Journal of E-Adoption, 9*(2), 17-30. https://doi.org/10.4018/IJEA.2017070102

Ziyan, F. S., & Kadri, A. (2025). Academic, emotional, and social consequences of bullying on special needs students. In S. Siddiqui & M. Kamran (Eds.), *Preventing bullying among children with special educational needs* (pp. 1-34). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-5315-8.ch001

APPENDIX: QUESTION/ITEMS USED BY THE STUDY

Construct	Measure
Perceived Usefulness	1. The performance of my study is (would) improve by using the technology 2. I have the knowledge necessary to use the technology 3. Using the technology would enhance my effectiveness in my study
Perceived Ease of Use	1. I am skilled at using a variety of technological tools for educational purposes 2. I would find the technology easy to use 3. It would be easy for me to become skillful at using AI technology
Intention to Use	1. I feel motivated to use digital tools as they help me overcome challenges in my learning process 2. I intend to take more courses using AI tool in the future 3. I intend to show others this AI application
Social Support	1. I feel supported by my teachers and peers when using AI-based assistive technologies in my learning. 2. I often rely on others, such as teachers or classmates, to help me use AI tools effectively in my education. 3. Having a strong support network increases my confidence and willingness to use AI assistive technologies.
Digital Literacy	1. I am confident in my ability to use digital tools, including AI-based assistive technologies, to support my learning. 2. I know how to evaluate whether the information provided by AI tools is accurate and trustworthy. 3. I have the digital skills necessary to use AI assistive technologies effectively in my studies.
Self-Efficacy	1. I am confident in my ability to learn and use AI-based assistive technologies to support my learning needs. 2. I believe I can use AI tools effectively to help me succeed in an inclusive learning environment. 3. I feel prepared to solve problems or fix issues that come up when using AI-based assistive technologies. 4. I am capable of choosing the right AI tools that suit my specific learning needs.

Construct	Measure
Motivation	1. I believe that AI-based assistive technologies can significantly improve my academic performance. 2. The availability of AI tools in my learning environment increases my enthusiasm for studying. 3. The opportunity to use AI assistive tools motivates me to actively participate in my learning process.

AUTHORS

Ma Kok Weng is a Malaysian computer scientist and full-stack developer from Seremban, holding a Bachelor's degree in Computer Science and Technology from Xiamen University Malaysia and a Master's in Business Analytics from Sunway University. Specializing in Java-based backend and frontend development, he combines technical expertise with analytical rigor to build robust digital solutions. Beyond his professional pursuits, Kok Weng harbors a deep fascination with astronomy and space exploration, balances his technical mindset with a passion for video games, and actively supports animal welfare through his involvement with Persatuan Haiwan Malaysia. His travels across Southeast Asia with family have further enriched his perspective, reinforcing his commitment to lifelong learning and innovation in technology.

Rexado Pramudita Julianton is a young professional from Indonesia who is originally from Kudus. He is an actuary and business analyst, holding a Bachelor's degree in Actuarial Science from UCSI University and a Master's degree in Business Analytics from Sunway University. His areas of specialization include analytics, statistics, probability, finance, and programming languages such as SQL and Python, which he utilizes to identify problems and develop optimal solutions. Beyond his professional pursuits, Rexado is actively involved in social causes. He volunteers as a mathematics tutor for underprivileged and out-of-school children and is a passionate advocate for health awareness. As a member of Allianz's awareness initiatives, he contributes to promoting the importance of insurance and financial protection. Rexado is also deeply interested in creativity and content creation. He produces light-hearted and thoughtful videos aimed at promoting mental health awareness. Through active engagement in various social groups and communities, he broadens his perspectives and keeps himself updated on current social issues and development.

Chan Xian Yang has completed his Master's degree in Business Analytics at Sunway University, Malaysia, where he also earned his Bachelor of Computer Science (Hons.) in Artificial Intelligence from Multimedia University. His research interests include artificial intelligence, machine learning, and data analysis. He has presented award-winning work on student engagement using facial and body gesture recognition at CITIC international conferences. He is passionate about applying data-driven solutions to enhance digital learning environments and optimize business decision-making.

Chai Yong Teng is a PhD candidate in the Faculty of Computer Science & Information Technology (FCSIT) at the University of Malaya. His research integrates machine learning and artificial intelligence to improve diagnostic accuracy and support preventive healthcare. He holds a Master of Business Analytics from Sunway University, where he received the Capstone Project Award – 1st Runner-Up (2024) and the Project Excellence Award – 1st Runner-Up (2023). With a strong foundation in business analytics, Yong Teng has experience in applying data-driven strategies to optimize performance in both commercial and healthcare settings. His passion lies in bridging the gap between data science and medical innovation to enhance patient outcomes and contribute to the future of predictive healthcare.

Dr. Muaadh Mukred is a senior lecturer and researcher with over 20 years of experience in academia and industry. He holds a PhD in Information Systems, along with Master's and Bachelor's degrees in Computer Science. His expertise lies in developing AI-powered, data-driven solutions using Python, Power BI, and other programming tools to support decision-making in government, education, and business. At Sunway University, he teaches and supervises postgraduate and undergraduate research in business analytics, artificial intelligence, and software development. His applied projects include smart dashboards, automation systems, and learning analytics tools that translate complex data into actionable insights. He has published more than 45 scholarly works in high-impact journals, reflecting his deep engagement in research focused on AI and technology adoption, digital transformation, big data analytics, and cybersecurity. He has also secured and contributed to several internal and external research grants, supporting interdisciplinary projects in digital governance, educational technologies, and public-sector innovation. Dr. Mukred actively develops AI-driven solutions that address operational inefficiencies, enhance strategic planning, and enable scalable innovation across various sectors, including healthcare, education, and industry. His work is driven by a commitment to solving real-world challenges through intelligent technologies. In addition to his academic and research contributions, he has held leadership roles in higher education, research centers, and international collaborations, further advancing innovation and academic excellence across disciplines.

Dr. Mikkay Wong Ei Leen is currently Head of the Department of Business Analytics at Sunway Business School, Sunway University. She is an experienced academic leader, educator, and avid researcher. Her academic credentials in engineering and management include a PhD in Management with a specific focus on the impact of training on employee commitment and retention. Throughout her academic leadership and service, she has brought forth strategic vision, operational effectiveness, and a staunch commitment to quality assurance. Her tenure as the Head of Department, Assistant Head, and former Program Leader has been characterized by efforts towards the promotion of curriculum innovation, developing academic staff, and ensuring program delivery excellence. On the same front, she has had a major role in quality audits, curriculum reviews, and accreditation readiness, which earned her the position of Chair of the Assurance of Learning Committee. She adopts a leadership approach that reflects collaboration, attention to academic standards, and the achievement of consistency between departmental initiatives and institutional objectives. Dr. Mikkay adopts and promotes a student-centric method of teaching coupled with instructional innovation by which she successfully manages considerable undergraduate cohorts. Her constant efforts and endeavors in teaching business statistics and analytics consistently generate high-quality learning experiences, manifesting in multiple Student Appreciation in Teaching Awards. Moreover, Dr. Mikkay's research involves bridging the gap between human resource development, learning analytics, and smart technologies in education and enterprise systems. Her research endeavors involve leading and collaborating with researchers on grant-funded research projects, the outcome of which are published in high-impact journals and reputable international conferences. Her effort towards this field is reflected in her meticulous and successful supervision of postgraduate Master's and PhD students.

Dr Abdu H. Gumaei received his PhD degree in Computer Science from King Saud University in 2019. He is an Assistant Professor in the Computer Science Department, Prince Sattam bin Abdulaziz University, Saudi Arabia, and Taiz University, Yemen. In the computer science department, he has taught many courses such as machine learning, AI, and programming languages. He has authored more than 90 journal and conference papers in well-reputed international journals. He received a patent from the United States Patent and Trademark Office (USPTO) in 2013. His main areas of interest are software engineering, disability research, image processing, computer vision, machine learning, networks, and the Internet of Things (IoT).