Smart Learning Environments

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Towards promoting innovation in inclusive education: behavioural intention of teachers towards adopting AI to teach students with learning disabilities in the UAE

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Abstract

The integration of artificial intelligence (AI) in education offers significant potential for identifying and supporting all students, including those with learning difficulties. Although discussions on the potential of AI to advance the learning of students are ongoing, AI usage among teachers to leverage it in the teaching of students with learning disabilities in nonwestern contexts, such as the United Arab Emirates, is unresearched. The study was guided by a unified theory of acceptance and use of technology to examine teachers' intentions toward adopting AI tools to enhance educational outcomes for students with learning disabilities in the UAE. Using a quantitative research approach, a structured survey was completed by 244 teachers from both public and private schools. The data were subjected to analyses, such as structural equation modelling, to test the structural validity of the unified theory of acceptance and use of technology. Moreover, confirmatory factor analysis, means, multivariate analysis of variance and path analysis were computed to explore the variables that impact the behavioural intentions of teachers. The findings provide support from instruments used to measure intentions towards AI. While social influence positively predicts intention, effort expectancy makes a negative but significant contribution to the variance in intention (social influence: $\beta = .32$; effort expectancy: $\beta = -.26$, $R^2 = 0.14$). The implications of the study for AI policy development and teacher development are discussed.

Keywords: Inclusive education, Technology, Artificial intelligence, Learning disability, UAE

Introduction

Artificial intelligence (AI) is no longer viewed merely as a futuristic add-on to education—it is increasingly recognized as a powerful tool to support students with diverse learning needs, particularly those with disabilities (Kadaruddin, 2023; Michel-Villarreal et al., 2023; Nalbant, 2021). Since John McCarthy first introduced the term AI in the 1950s, AI has evolved from a theoretical concept to a tool now embedded in fields as varied as medicine, engineering, and education (Ahmad et al., 2021; Pothen, 2021). In today's classrooms, generative AI is being explored for its efficiency, ability to personalize learning experiences, simulate human-like feedback, and help educators adapt instruction to the unique pace and strengths of each learner (AlAli & Wardat, 2024; Kadaruddin, 2023; Pothen, 2021; Zhai et al., 2021). This is especially valuable in inclusive settings where a one-size-fits-all model often fails to meet the needs of students with cognitive, sensory, or language-related challenges (Ahmad et al., 2021; Michel-Villarreal et al., 2023). Researchers are beginning to push beyond a purely functional view of AI, instead arguing for more relational, human-centered use—where AI works alongside teachers as a cognitive partner, enhancing their ability to support learners rather than replace them (Cukurova, 2025; Lim et al., 2023). In many countries, including the United Arab Emirates (UAE), teachers struggle to support the teaching of students with diverse needs in classrooms (Loyd et al., 2024; Massouti et al., 2024a). This finding lends support to exploring the preparedness of teachers to use AI to support students with learning disabilities.

Learning disability/difficulty (LD) constitute the largest disability group globally in schools. Learning difficulty typically refers to struggles or barriers that hinder a student's ability to grasp academic concepts or skills at the same pace or level as their peers (Grigorenko et al., 2020; Krämer et al., 2021; Mähler, 2021). On the other hand, learning disability is a specific neurological condition that affects how an individual receives, processes, or communicates information (American Psychiatric Association, 2013; Niazov et al., 2022; Orim et al., 2023). However, in this study, both will be used interchangeably. Both learning difficulty and learning disability can be categorized under the umbrella of a specific learning disorder. In this study, learning difficulty and learning disability are used interchangeably, and operationalized difficulties associated with learning, reasoning, writing and arithmetic are used (Bozatlı et al., 2024; Inês et al., 2022; Schmeisser & Courtad, 2023). The condition encompasses dyslexia, dysgraphia and dyscalculia. Currently, it is surmised that the number of students with difficulty is on an upwards trajectory. During the 2021- 2022 school year, approximately 7.3 million students in the United States were accommodated under the Individuals with Disabilities Education Act (IDEA), accounting for approximately 15% of the total public-school enrollment (National Center for Education Statistics., 2023). Among these students, approximately 33% who received special education assistance were identified as having specific learning disabilities. In the UAE, according to the Statistics Centre—Abu Dhabi, as of September 2022, there were 6,145 students of determination enrolled in government schools across the Emirate of Abu Dhabi. Of this total, 3,819 students were identified as having LD, making it the most common type of disability in these schools (Office of Homeland Security Statistics, 2023). These findings indicate that a significant number of students with disabilities in schools are living with LDs.

Students with LDs often face unique challenges in the educational setting (Aldakhil, 2024; Aro et al., 2022; Nevill & Forsey, 2023; Page et al., 2021). Many children have recently faced noticeable difficulties in learning basic skills such as reading, writing, and arithmetic (Moll et al., 2020; Muktamath et al., 2022; Snowling et al., 2020). Children experiencing learning difficulties struggle to meet academic expectations due to various factors, including sensory impairments, behavioral or emotional challenges, language barriers, frequent absences, poor instruction, or unsuitable curricula (Maughan et al., 2020; Moll et al., 2020). It is very important to acknowledge and identify these difficulties to establish appropriate interventions (Gabriely et al., 2020; Grigorenko et al., 2020; Miciak & Fletcher, 2020). Importantly, each student's experience with learning difficulties or disabilities is unique, and they may require personalized support and accommodations to thrive academically (Bernacki et al., 2021; Brown et al., 2020; Khouri et al., 2022; McGahee et al., 2021). As mentioned by Auspeld (2022), learning disabilities in children manifest as enduring challenges in particular academic domains due to an underlying neurodevelopmental condition influenced by a combination of genetic, cognitive, and environmental factors. A key characteristic of these disabilities is their persistence despite receiving appropriate educational support and interventions (Francis et al., 2019; Hentges et al., 2021). Therefore, with tailored support and evidence-based teaching methods, these children can reach their age-appropriate academic potential.

Generative AI is opening new possibilities for LDs by helping individuals personalize, adapt, and democratize access to education in ways that were previously difficult to achieve at scale (AlAli & Wardat, 2024; Chen et al., 2020; Michel-Villarreal et al., 2023; Nalbant, 2021). Across a growing body of research, there is a shared recognition that AI tools—from conversational agents such as ChatGPT to visual recognition systems such as Seeing AI—can support students who learn differently by adjusting content to meet their needs, offering multimodal feedback, and removing barriers to participation (Michel-Villarreal et al., 2023; Nalbant, 2021). For students with conditions such as dyslexia or visual impairments, these technologies can provide continuous, judgment-free assistance with reading, writing, and comprehension while also allowing for repetition and pacing tailored to the learner. More broadly, AI-enhanced platforms such as Classcraft offer gamified learning environments that increase engagement and can be especially effective for students who struggle in conventional classroom formats (Nalbant, 2021). What is particularly promising is how AI enables teachers to respond to student needs in real time—drawing on learner analytics, adaptive feedback, and content generation—to create more inclusive learning journeys (AlAli & Wardat, 2024; Chen et al., 2020).

In this context, predictive models powered by AI are also essential for identifying at-risk learners before they experience academic failure. The study by Pallathadka et al. (2022) emphasized that analysing student performance data can help educators and institutions intervene early with targeted support plans—an approach particularly relevant for students with learning disabilities, who may need more individualized attention than traditional systems typically provide. Rather than relying on a single approach for all students, AI makes it possible to dynamically adjust instruction on the basis of evolving learner profiles, preferences, and abilities. Nevertheless, researchers caution that the benefits of personalization must be balanced with thoughtful oversight—raising concerns about data privacy, bias in algorithmic design, and the need for strong ethical frameworks (AlAli & Wardat, 2024; Cukurova, 2025; Kadaruddin, 2023; Lim et al., 2023). As the field evolves, scholars emphasize that AI should not be treated as a replacement for good teaching but rather as a support system that amplifies the ability of educators to meet the needs of all students, particularly those historically underserved by traditional methods (Chen et al., 2020; Lim et al., 2023; Zhai et al., 2021). In this context, generative AI is not simply a tool—it is emerging as a bridge to more equitable, flexible, and accessible education for learners who need it most.

Although inclusive education is gaining momentum worldwide, teachers continue to navigate a tangled set of challenges in regard to supporting students with learning disabilities (Alsarawi, 2024; O'Sullivan et al., 2023; Oswal et al., 2025; Rashid & Wong, 2022; Russell et al., 2023). One of the most commonly reported struggles is the gap between what educators learn during their training and what they actually face in the classroom. In contexts such as Saudi Arabia, preservice teachers often feel thrown into complex teaching environments with strong theoretical knowledge but little clarity on how to apply it, especially when mentorship and school leadership are inconsistent or unclear (Alsarawi, 2024). This disconnect becomes even more pressing when teachers are expected to assess and support students with diverse needs but lack the confidence or technical skills to do so. Rashid and Wong (2022) highlight this gap in the Malaysian context, where teachers report difficulty understanding and implementing individualized education plans, particularly in regard to tracking student progress. In the UAE, teachers face a number of challenges when trying to apply inclusive education in their classrooms (Alborno, 2017; Alhammadi, 2024; Massouti et al., 2023). In previous studies, teachers claimed that they did not have enough knowledge, resources, or training to support students with special needs properly (DeCarlo et al., 2023; Hehir et al., 2016). Even though the country has made strong efforts to promote inclusion, many teachers still feel unprepared and unsure about how to teach students of LD (Alborno, 2017; Massouti et al., 2023).

Amidst the growing recognition of technology as vital to promoting the learning of students with LDs, teachers struggle to adopt it in their classrooms. Even in higher education systems that are committed to inclusion, such as those in the UAE, practical implementation remains uneven. Faculty are often undertrained, assistive tools are underused, and institutional follow-through to inclusive policies is weak (Oswal et al., 2025). This trend holds true across many systems: educators frequently cite a lack of preparation to teach students with complex needs such as autism spectrum disorder or speech impairments—conditions that demand not only more nuanced instructional strategies but also consistent support (Russell et al., 2023). Even when teachers are motivated to try new approaches, the lack of accessible assistive technology continues to hold them back (Beyene et al., 2023; Fernández-Batanero et al., 2022). As O'Sullivan et al. (2023) noted in the Irish context, many teachers are not just unfamiliar with assistive tools—they do not even have the vocabulary to articulate what kind of training or resources they need. That kind of disconnect—between what teachers are being asked to do and what support systems actually exist—makes it clear that inclusion is still far from guaranteed. More than goodwill is needed: educators require sustained professional development, consistent access to resources, and stronger collaboration between policymakers, leaders, and classroom practitioners (Opoku et al., 2021; X. Zhang et al., 2020). Without that, inclusion risks becoming a policy goal that outpaces everyday reality. However, this is also where generative AI can begin to bridge the gap—offering teachers real-time support, accessible instructional tools, and adaptable learning environments that respond to diverse student needs. When thoughtfully integrated, AI has the potential to ease the weight on educators and extend the reach of inclusive education—not by replacing human effort but by reinforcing it.

The UAE government has demonstrated commitment to the implementation of inclusive education through the development of policies and investment in resources and teacher development. Moreover, the smart learning environment has been implemented as a way to make up-to-date technology available to facilitate quality teaching and learning for diverse students. However, the preparedness of teachers to leverage generative AI as part of an effort to meet the learning needs of diverse students has rarely been studied. Teacher preparedness is measured via intention as a proxy. Indeed, intention mirrors actual realities; once intentions are favourable, it could be inferred that teachers will be in a position to teach diverse students using generative AI. The purpose of this study is to explore the intention of teachers to use AI to support the teaching of students with LDs in regular schools in the UAE.

Theoretical framework

The current study was guided by the unified theory of acceptance and use of technology (UTAUT). The theory has been widely used in research on technology and its intended usage among a given population (Alowayr, 2022; Hewavitharana et al., 2021; Kimiagari et al., 2022). Since discussions on AI usage to support the learning of students with LDs are in their infancy, especially in the UAE context, UTAUT was deemed a useful theory for this study. The authors attempted to understand the fidelity of UTAUT before considering theoretical advances in the field of technological application in education.

The origin of UTAUT could be linked to two theories: the theory of planned behaviour and the technology acceptance model (Marikyan & Papagiannidis, 2023; Rejali et al., 2023). For instance, the theory of planned behaviour was proposed by Ajzen (1991) to measure individuals' intentions towards a given phenomenon. The TPB is an extension of the theory of reasoned action, which defines behaviour as a product of two types of beliefs, behavioural beliefs and normative beliefs (Ajzen, 1991, 2011, 2020). Behavioural belief is defined as one's perception, which is influenced by the information available to them and their belief about the outcome of their participation in a given behaviour (Ajzen, 1991, 2011, 2020). Normative belief is also defined as the influence of significant others on one's behaviour (Ajzen, 1991, 2011, 2020). For instance, individuals such as society or policymakers could influence one's action. However, in the conception of the TPB, Ajzen (1991) contended that a third belief, perceived behaviour control, could have direct or indirect effects on behaviour. Perceive behaviour control was defined as one's assessment of their capacity to engage in a given behaviour (Ajzen, 1991, 2011, 2020). Therefore, Ajzen argued that three related beliefs, i.e., behavioral, normative and perceived behavioral control, combine to predict one's intention toward a given behavior (Ajzen, 1991). This theoretical foundation highlights the development of UTAUT, which perceives behaviour as a product of other variables.

Davis's technological acceptance model also informed the development of UTAUT. Earlier, in the development of the TAM, Davis argued that the tenets of technology acceptance were perceived ease of use, attitude, perceived usefulness, behavioural intentions and actual use of technology (Davis, 1989). According to Davis, the perceived usefulness and perceived ease of use of technology combine to predict one's attitude towards technology. Moreover, perceived ease of use will be mediated through perceived usefulness to predict both types of behavioural intentions, which would also impact the actual usage of technology.

Notably, the TAM has undergone several evolutions. For example, Davis conceived earlier that the TAM is related to one's motivation and the characteristics of the devices. However, Davis modified and aligned the tenets directly with the TPB. While eliminating subjective norms, Davis introduced new concepts: perceived usefulness and perceived ease of use. Perceived usefulness refers to one's perception that using a given device could enhance the efficiency or execution of a given behaviour. Perceived ease of use was also defined as one's perception of their capacity to operate a given device. Davis argued that perceived ease of use and perceived usefulness mediate through attitude to predict one's intentions toward a given device.

However, Davis conducted a study and realized that attitude had a very weak effect on intention towards a given technology. Following this study, Davis argued that, perhaps, perceived ease of use and perceived usefulness directly predict intentions without mediating through attitudes towards technology. Consequently, other researchers added to the TAM to ascertain its fidelity. One notable one was Venkatesh and Davis, who added additional variables to test its impact on behavior: self-efficacy, perceived enjoyment, perception of external control, anxiety, playfulness and usability. These developments resulted in the conception of UTAUT.

The UTAUT is believed to be composed of four tenets: effort expectancy, social influence, facilitating conditions and performance expectancy. These tenets were operationalized in this study. In this study, facilitating conditions were explained as one belief that their institution has the requisite infrastructure to support them in adopting AI to support students with LDs. Additionally, performance expectancy refers to the perception that AI will help them effectively support students with LDs in their classrooms. Moreover, social influence was defined as the influence of significant others on their decision to use AI to support students with LDs. Finally, effort expectancy was defined as the ease with which individuals could use AI to support the learning of students with LDs.

In this study, the contributions of these four variables to the variance in intention towards AI usage were explored (see Fig. 1). In previous studies, the contributions of performance expectancy, effort expectancy, social influence and facilitating conditions to the variance in behavioral intentions have been explored (towards using AI to support the learning of students Abbad, 2021; An et al., 2023; Chatterjee & Bhattacharjee, 2020; Yakubu et al., 2025). In different contexts, the predictors of behavioural intentions have not been uniform. For example, in a study of the intention of students in higher education towards using AI, facilitating conditions emerged as a predictor of behavioural intentions (Chatterjee & Bhattacharjee, 2020). However, performance expectancy made no significant contribution to the variance in behavioral intentions. Conversely, An et al. (2023) assess the intention of language teachers towards using AI to support students' teaching. They reported that performance expectancy, social influence and other variables were significant predictors of behavioural intentions. However, effort expectancy did not make a unique contribution to the variance in behavioral intentions. It is useful to contend that possible reasons for differences in the predictors of behavioural

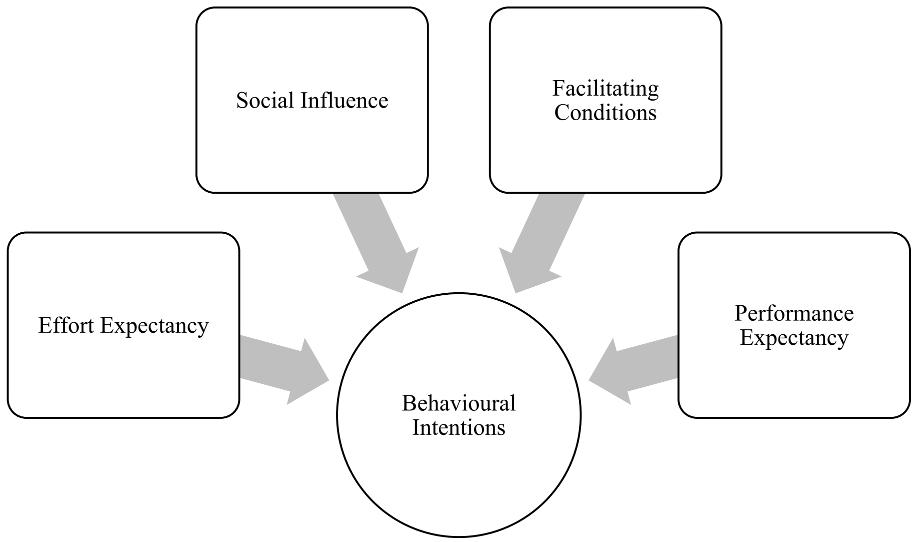

Fig. 1 Summary of UTAUT

intentions are the environment or areas in which AI is used to support students' learning. In all these areas, the use of AI has generally been studied in the context of language learning or supporting students' learning. Teaching students with LDs has its own challenges and thus the potential for different variables to influence intentions. The lack of uniformity between the factors predicting behavioural intentions lends support for further exploration in areas such as the role of AI in supporting the learning of students with LDs.

On the basis of Ajzen's reasoning in the conception of the TPB, the following hypotheses were tested:

> **H1**: *Performance expectancy, social influence, effort expectancy and facilitating conditions are combined to predict the behavioral intentions of teachers toward supporting students with LDs.*

Additionally, Ajzen (2011) argued that background variables such as the gender of participants could provide insight into intentions. Moreover, demographic variables could also impact the individual predictors of intentions. Within the context of AI in education, the predictors have been unilinear, which justifies an examination of differences between participants on the basis of their background variables. In particular, environments differ; thus, teachers, on the basis of their circumstances, could have different perceptions of integrating AI in the teaching of students with LDs. Consequently, the following hypotheses were formed:

H2: Teachers can differ in performance expectancy, social influence, effort expectancy and facilitating conditions in regard to teaching students with LDs.

Teachers' intention towards AI usage

In recent years, as AI tools weave their way into everyday teaching practices, the questions of what drivers, barriers, and uptake have gained scholarly interest. To unpack this, scholars have focused heavily on the UTAUT (Venkatesh and Davis, 2003) and its extended version, UTAUT2 (Venkatesh and Xu, 2012), across a range of studies conducted in countries such as Indonesia, China, Nigeria, Israel, Bangladesh, and India; four constructs repeatedly emerge as central to teachers' intentions to embrace AI: performance expectancy, effort expectancy, social influence, and facilitating conditions. Among these factors, performance expectancy stands out as the most consistent driver of adoption. With respect to lesson planning in Ghana (Acquah et al., 2024), student assessment in the Middle East (Khlaif et al., 2024) or experiments with generative AI in Chinese universities (Xu et al., 2024), the perceived benefits of AI for boosting efficiency and teaching quality appear to strongly influence teachers' willingness to use it. Even in broader syntheses such as Nikolic et al. (2024) systematic review, performance expectancy remains central, reinforcing that perceived usefulness is a key variable that is central to AI adoption by teachers (Nikolic et al., 2024).

The contributions of the other variables are mixed. For example, the impact of effort expectancy on teachers' intentions differs across studies and contexts. In several cases—such as those by Gupta (2024) in India and Cabero-Almenara et al. (2024) in Spain—teachers were more inclined to adopt AI when they found it straightforward to use. Conversely, in a study of Indonesian EFL lecturers, effort expectancy had no significant effect, possibly because a baseline of digital familiarity made usability a nonissue (Zaim et al., 2024). Moreover, Xu et al. (2024) findings from China revealed that although ease of use mattered, it was not enough on its own—actual adoption required ongoing institutional reinforcement and established habits. Moreover, with respect to social influence, in some settings, such as Indian higher education, peer approval clearly supports uptake (Gupta, 2024). Even when social influence was statistically significant, as shown in Rana et al. (2024) and Zaim et al. (2024), it often had the lowest mean score. These results underscore that community dynamics and visible role models play a vital role in shaping how AI is perceived and whether it is embraced. With respect to facilitating conditions, studies conducted in Nigeria (Adigun et al., 2025) and Bangladesh (Rana et al., 2024; Xu et al., 2024) have consistently reported that institutional shortcomings limit their ability to experiment with AI, even when their attitudes are positive. On the other hand, studies from China (Xu et al., 2024) and India (Gupta, 2024) have shown that strong infrastructural support could translate behavioral intention into sustained use. In short, motivation means little if systems are not built to catch and sustain that momentum.

Another area of complexity is the influence of teachers' demographic characteristics on the intentions of teachers (Bamasoud et al., 2025; Konca et al., 2025). Across teacher preparation settings, familiarity with generative AI appears to develop gradually as educators deepen their teaching experience and gain exposure to institutional conversations around AI use. Studies of university lecturers, for example, have shown that those with more teaching experience tend to report greater confidence in evaluating student use of AI (performance expectancy) and in navigating its ethical implications (effort expectancy), whereas mid-career educators often demonstrate the highest levels of hands-on experimentation with AI in lesson planning and assessment design (Bamasoud et al., 2025). Moreover, research with preservice teachers highlights that the national and institutional environment, rather than individual traits such as age or academic year, strongly influences how future educators understand and interact with AI. Differences in exposure—whether through everyday digital life, training opportunities, or programme-level expectations (social influence)—play a decisive role in shaping whether educators see AI tools as meaningful, manageable, or relevant (effort expectancy) to their future practice (Konca et al., 2025).

The role of the professional environment becomes even clearer when educators possess strong academic training and digital literacy, and perceptions of usefulness (effort expectancy) and ease of use (performance expectancy) tend to support positive attitudes toward integrating AI into teaching and research. However, several studies have shown that familiarity alone is not enough (Hazzan-Bishara et al., 2025; Møgelvang et al., 2025; Sarabdeen, 2025). Bishara's large-scale work with in-service teachers demonstrates that although most educators are already informally engaging with AI, many are doing so without structured guidance, highlighting the importance of institutional support in building both confidence and ethical practice (facilitating conditions). Similarly, Møgelvang reported that participation in a university-sponsored AI training course significantly increased actual GenAI use and, importantly, reduced differences previously associated with age, professional role, or prior experience. In this view, adoption is not determined by who educators are, but by facilitating conditions, whether institutions create sustained opportunities for learning, experimentation, and reflection.

A similar pattern appears in studies that look more closely at educators' sense of agency and motivation when working with AI (Al-Amri & Al-Abdullatif, 2024; Bhat et al., 2024). Rather than adopting AI simply because it is available, many educators seem to take it up when they feel that it fits their teaching style or supports decisions, which they already value. In Bhat's multicampus study, for example, faculty members described using ChatGPT in ways that aligned with their disciplinary habits—such as drafting research prompts or experimenting with explanation techniques—yet several also noted that they were cautious about discussing this use openly. Their hesitation was not necessarily about the tool itself but about how colleagues or administrators (social influence) might view it. Moreover, a related dynamic emerges in the K–12 settings. In Al-Amri's work with teachers in Saudi Arabia, differences in age or teaching experience did not strongly predict behavioural intentions towards using chatbots. Instead, teachers mentioned curiosity, a sense of enjoyment, and the feeling that they could "make the tool work for them" as more influential in their decisions (effort expectancy—EE; intrinsic motivation shaping BI). In other words, what mattered was whether teachers saw AI as something that could genuinely support their classroom routines, not whether they fit a particular demographic profile. Across these studies, adoption appears to hinge on educators' everyday professional judgment—how they read their context, how much room they feel they have to experiment with, and whether they can use AI without compromising their pedagogical identity.

Teachers' use of AI to support the teaching of students with learning disabilities

AI is increasingly viewed as a supportive partner in inclusive education, particularly in assisting teachers who work with students with LDs. Across a growing body of literature, AI has emerged as a means to enhance pedagogical responsiveness and equity (Alam & Mohanty, 2023; Roshanaei et al., 2023; Wu, 2024; J. Zhang & Zhang, 2024). Moreover, intelligent tutoring systems, speech-to-text technologies, and emotion-sensing tools are being used to adapt instructions to suit the uniqueness of students with LDs (Alsolami, 2025; Bressane et al., 2024; Fitas, 2025; Sharma et al., 2023; Song et al., 2024). For example, an AI-powered decision support system helps to understand students' learning behaviors—enabling teachers to customize instruction on the basis of real-time learner data (Bressane et al., 2024). Similarly, the study by Alsolami (2025) highlights how culturally adapted, gamified AI tools help educators improve academic outcomes among students with mild intellectual disabilities, reinforcing AI's role in reshaping instruction through localized, student-centered design.

In the context of these developments, teachers are increasingly empowered to make informed decisions about instructional pacing, personalized learning, progress monitoring, accessible content delivery, and student engagement through the use of AI tools (Fitas, 2025; Harkins-Brown et al., 2025; Li et al., 2024; Zhao et al., 2025). Scholars have highlighted how educators leverage text-based tools, robotics, speech recognition, visual impairment tools, and other assistive technologies to support students with diverse LDs, including ADHD, autism, dyslexia, and sensory or intellectual impairments (Sharma et al., 2023; Voultsiou & Moussiades, 2025). These tools help simplify complex concepts, summarize texts, personalize instruction, and promote both cognitive and social development. At the same time, AI is easing the administrative workload, which often limits inclusive teaching practices. As Fitas (2025) and Harkins-Brown et al. (2025) observe, the automation of tasks such as drafting IEPs, adapting lessons, and tracking student progress enables teachers to redirect their time and energy toward more meaningful, student-centered interactions.

These benefits are particularly evident in special education settings where teachers often juggle large caseloads, develop individualized plans, and manage heavy preparation demands (Fitas, 2025; Sharma et al., 2023). However, despite the promise of saving time, several studies caution that the effectiveness of AI depends on how well educators are supported in learning to use it. A study by Voultsiou and Moussiades (2025) emphasized that effective AI use in education involves more than technical proficiency. It requires careful attention to how tools align with student needs, protects data privacy, and mitigates potential biases in decision-making. Sharma et al. (2023) noted that AI works best when it complements what teachers already do, such as noticing what matters to students, adapting to their needs, and supporting them emotionally. When used with care, AI can help teachers create learning spaces that are more flexible and attuned to students who might otherwise feel sidelined in traditional classrooms. However, within the context of the implementation of inclusive education, research on teachers' intention to adopt AI to promote the learning of students with LDs is very rare.

Despite this growing body of work, a notable gap remains: very few studies examine AI adoption specifically among teachers in special education contexts, where instructional decision-making, student communication needs, types of disability and multimodal forms of support differ significantly from those in general education settings. Special education teachers routinely adapt materials, scaffold communication, and tailor learning pathways in ways that may uniquely shape how they interpret the affordances and risks of AI. However, their perspectives are largely absent from existing research. The present study addresses this gap by examining how teachers in the UAE understand, evaluate, and engage with generative AI tools within their instructional and support work, offering insight into a professional group whose expertise and pedagogical orientation may reveal different forms of AI adoption than those documented in mainstream educational settings.

Current study

The aim of the study reported here is to assess the intention of teachers towards using AI to support the teaching of students with LDs. The current study is relevant for two reasons. First, the UAE is one of the leading countries in the Arab world that has developed numerous policies intended to promote the teaching of students with LDs (Corpuz & Maher, 2024; Massouti et al., 2023, 2024b). However, students are not attaining the requisite assistance from teachers. This makes the usage or integration of AI vital in an attempt to promote the effective implementation of inclusive education. Second, the UAE has implemented a smart learning environment, which involves tailoring technology and pedagogical instruction in the teaching of students with LDs. The implementation of SLE forms part of the government to develop an innovative society where technology is central to service delivery (Al Batayneh et al., 2021; Al-Naqbi & Mustaffa, 2021; Halder Adhya et al., 2024; Radwan et al., 2023). The use of AI is integral in the implementation of smart learning environments. Unfortunately, research on the preparedness of teachers to adopt AI to teach students with LDs is limited. The study was guided by the following research questions:

1. What is the level of intention (effort expectancy, social influence, facilitating conditions and performance expectancy) of teachers towards using AI to support students with LDs?
2. What are the differences in the demographic characteristics (see Table 1: gender, age, etc.) of teachers in terms of their intentions (effort expectancy, social influence, facilitating conditions and performance expectancy) to use AI to support students with LDs?
3. What are the predictors of the intention (effort expectancy, social influence, facilitating conditions and performance expectancy) of teachers toward using AI to support students with LDs?

Method

Study participants

The study focused on teachers employed in both public and private schools across the Emirate of Abu Dhabi, where inclusive education practices are in place to support students with learning difficulties. Abu Dhabi was chosen as the research site because of its educational diversity, which spans urban and suburban settings and includes institutions following a range of curricula and policies. By involving both government-funded and privately operated schools, this research aimed to capture a broad spectrum of teacher perspectives on the integration of AI tools within varied teaching contexts and models of inclusion.

Table 1 Demographic characteristics of study participants

	Frequency (N = 244)	Percentage
Place of origin		
Teachers from UAE	107	44%
Teachers from outside UAE	137	56%
Gender		
Male	101	42%
Female	143	58%
Age		
20–25 years	63	26%
26–30 years	60	25%
31–35 years	47	19%
36 years and above	74	30%
Marital status		
Single	119	49%
Married	125	51%
Teaching Experience		
0–5 years	101	42%
6–10 years	72	30%
11–15 years	33	14%
At least 16 years	38	16%
Qualification		
Bachelor	134	55%
Masters	83	34%
Others	27	11%
Teacher Type		
Special education teachers	67	27%
Early childhood teachers	52	21%
General teachers	83	34%
Others	42	17%
School type		
Public school	115	47%
Private school	129	53%
School location		
Abu Dhabi	116	48%
Al Ain	111	45%
Al Dhafra	17	7%

Participant recruitment was conducted through a social media platform widely used by educators in the region. Teachers were invited to participate in the survey if they met the following criteria: (a) they were either general or special education teachers; (b) they taught full-time in a school located within Abu Dhabi; (c) they had students with learning difficulties in their classrooms; and (d) they were capable of providing informed consent to participate in the study.

Altogether, 244 teachers working in inclusive education settings participated in the research. Table 1 provides a detailed breakdown of participant demographics. To highlight a few key figures, 56% of the participants were non-Emirati, whereas 44% were UAE nationals. In terms of gender, 58% identified as female and 42% as male. Marital status was nearly evenly split, with 51% reporting that they were married and 49% reporting that they were single (refer to Table 1 for further demographic details).

Instrument

The survey used for data collection consists of three sections. The first section collected the demographic information of the teachers (see Table 1). The demographic information included in this study was obtained from previous studies and recommendations from experts who reviewed the instrument before data collection.

The second section, referred to as teachers' intention towards using AI, was developed on the basis of the UTAUT framework (An et al., 2023). In a Chinese study, An et al. (2023) reviewed the literature and identified items that measure each of the domains of the UTAUT. The intention to use AI (N = 19) is measured with five subscales. The first subscale is behavioral intention (n = 4), which measures how willing and motivated teachers are to use AI in the future and whether they want to learn more and share what they know. The second subscale is performance expectancy (n = 4), which measures how much teachers believe that AI will make their teaching better and more effective. Effort expectancy (n = 4) concerns how easy or hard teachers perceive the usage of AI tools in their classrooms. Social influence (n = 3) refers to how much teachers feel encouraged or pressured by their coworkers, principals, or others to start using AI. The facilitating conditions (n = 4) focus on whether teachers believe that they have enough resources, support, and equipment to use AI well.

Each question uses a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The items were positively worded, with a mean score of at least 4 interpreted as high intention. The entire survey was designed to take approximately 10 -15 min.

An et al. (2023) used an instrument to measure language teachers' behavioural intentions towards using AI to teach students generally. However, in this study, the items were adapted to suit the purpose of this study. For example, with respect to performance expectancy, AI can help me improve the quality of teaching, which is calibrated as follows: 'AI can help me improve the quality of teaching for students with a learning disability/difficulty'. For example, expert review by three researchers in the field of educational technology and a pilot test conducted among preservice teachers revealed that the items were clear and understandable.

Procedure

A proposal for the study was sent to X's Ethical Approval Committee for clearance to conduct the research (X). All ethical guidelines, including confidentiality, voluntary participation, and informed consent, were met. Following ethical approval, a research proposal, along with the survey instrument, was sent to schools across Abu Dhabi, Al Ain, and Al Dhafra, who invited them to participate in this study. Schools were contacted through official channels, including emails, school administrators, and professional networks, to request their participation in the study.

Once approval was obtained from the participating schools, the teachers were invited to complete the survey electronically via a secure online platform such as the school's WhatsApp groups and email addresses. The survey was shared by the school administrator on behalf of the research team. These media outlets are official channels through which schools share information with teachers. The survey was accompanied by a detailed consent form, outlining the purpose of the study, the voluntary nature of participation, and confidentiality assurances. It is essential to indicate here that personal information about participants, such as name, school name, location and other identifiable information, was not collected. Additionally, the participants were assured that the data would be stored in a OneDrive belonging to X University, which is passworded, protected and accessible only to the research team. The participants were given sufficient time to complete the survey at their convenience, ensuring minimal disruption to their professional responsibilities. To encourage participation and maximize response rates, reminders were sent periodically. Data collection was conducted over a four-month period (March 2025–June 2025).

Data analysis

After the data collection, the online data were transferred to Microsoft Excel for cleaning. In all, 257 teachers completed the survey. However, 13 entries were deleted because of incompleteness. The data were subsequently transferred to SPSS version 29 for data analysis. Initial assessment of normality via histograms, boxplots and Q–Q normality revealed that the data were normally distributed. This underscores the use of parametric analysis to answer research questions.

Before the research questions were answered, the instruments were validated via confirmatory factor analysis (CFA). The instrument was revised and translated for the purpose of this study. It was necessary for the instrument to be validated before it could answer the research questions. The appropriateness of the CFA model was determined via the following cut-offs: chi-square ≤ 5; Tucker–Lewis index (TLI) and comparative fit index (CFI) $\geq .90$; and root mean square error of approximation (RMSEA) and standardized root mean squared residual (SRMR) between .03 and .08. The individual loading for each item was at least .50.

For research Question 1, mean scores were calculated to explore behavioral AI intentions. Here, a composite mean of at least 4 was interpreted as high AI-intentions.

For research question 2, multivariate analysis of variance was computed to assess the effects of demographic variables on behavioural intentions (Pallant, 2020). To avoid committing Type 1 error, for behavioural intentions, the alpha value was set at .01 (two domains divided by .05). The weights of the differences (Pallant, 2020) between participants were interpreted as small (.01—.03), moderate (.04—.08) or large (at least .10).

For research question 3, hierarchical regression was computed to explore the impact of demographic variables (Pallant, 2020) on behavioural intentions. In step 1, the other tenets of AI intentions were regressed directly on behavioural intentions. In step 2, demographic variables were added to the model to ascertain their impact. Assumptions of homogeneity of variance, linearity, multicollinearity and homoscedasticity were not violated (Pallant, 2020). Additionally, path analysis was computed to complement hierarchical regression. The fit indices discussed earlier were observed to ensure that they were not violated. The magnitude of the weight of the result from both the hierarchical regression and path analysis were assessed via the R square, which was interpreted as follows (Chin, 1998): strong ($> .67$), moderate ($\leq .67$) and weak (.19).

Results

CFA was computed to explore the fit of the data for this study. The calculation of the CFA results was as follows: chi-square = 3.16 (CMIN = 448.06, df = 142), CFI = .95, TLI = .94, RMSEA = .09 and SRMR = .03. The individual items loaded above .50 and thus support its appropriateness for the study (see Fig. 2). The data were deemed suitable for the current study.

The next step was to assess the configural measurement invariance estimate. This was done to check whether the instrument was consistent across different demographic groups. For this purpose, the gender and nationality of the teachers who participated in this study were selected for the invariance estimate. For gender, the fit indices were as follows: male (chi-square = 2.86 (CMIN = 2033.35, df = 710), CFI = .93, TLI = .92, RMSEA = .05 and SRMR = .03) and female (chi-square = 2.86 (CMIN = 2033.35, df = 710), CFI = .93, TLI = .92, RMSEA = .05 and SRMR = .03).

Following the CFA, compositive reliability, convergent validity and discriminant validity were computed. This was done via Gaski's validity master sheet (https://statwiki.gaskination.com/index.php?title=Main_Page). Acceptable composite reliability is a score above .70; convergent validity is an average variance extracted score above .50 and factor loading for each item of at least .50; and discriminant validity is the square root of the

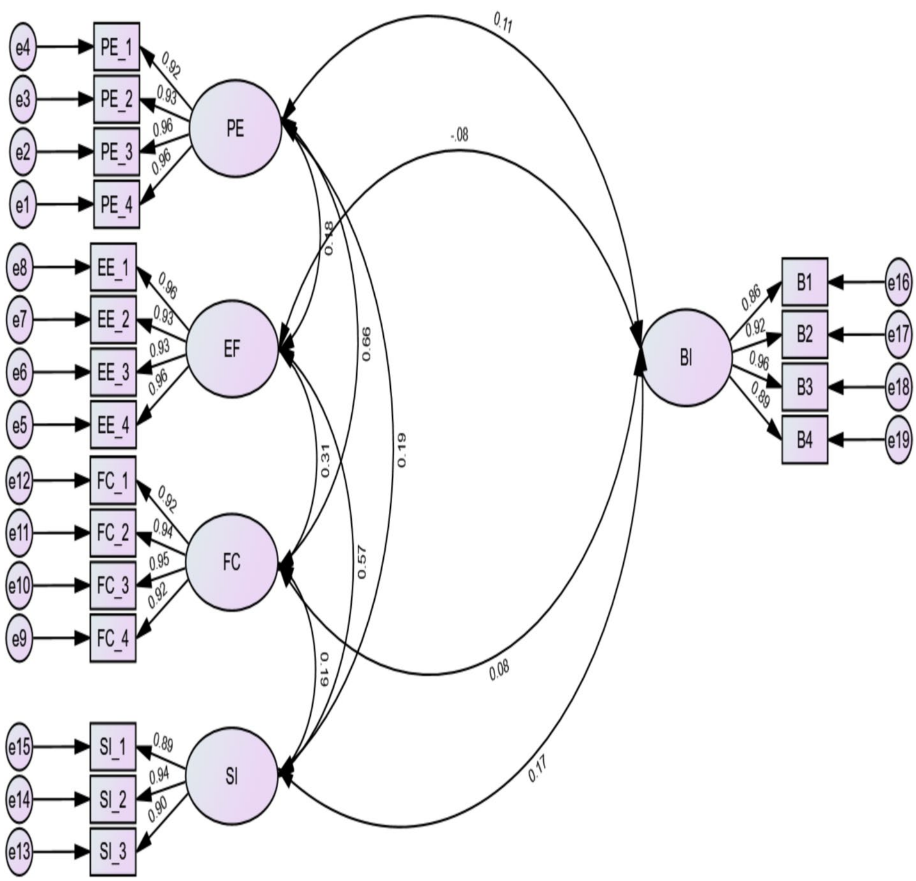

Fig. 2 Confirmatory factor analysis for intention towards AI *Note*: PE, Performance Expectancy; EF, Effort Expectancy; FC, Facilitating Conditions; SI, Social Influence; BI, Behavioral Intention

Table 2 Summary of composite, convergent and discriminant validity

	CR	AVE	EF	PE	SI	FC	BI
EF	.97	.89	.95##				
PE	.97	.89	.18	.94##			
SI	.94	.84	.57	.19#	.91##		
FC	.96	.87	.31	.66#	0.19#	0.93##	
BI	.95	.83	− .08	.11#	0.17#	0.08#	0.91##

CR, compositive reliability; AVE, average variance extracted; PE, Performance Expectancy; EF, Effort Expectancy; FC, Facilitating Conditions; SI, Social Influence; BI, Behavioral Intention; #, inter-construct correlations; ##, discriminate validity

average variance extracted greater than the interconstruct correlations. From Table 2, the composite reliability was above the .70 threshold, the convergent validity was also .50, and the square root of the AVE was above the interconstruct correlation. Here, it could be argued that composite reliability, convergent validity and discriminant validity were attained.

The reliability of the scale computed via Cronbach's alpha yields the following results: Performance Expectancy (.97); Effort Expectancy (.97); Facilitating Conditions (.96); Social Influence (.94); and Behavioral Intention (.95).

Teachers' level of intention towards AI

The mean scores for the items on teachers' level of intention towards AI were as follows: Performance Expectancy (M = 3.58, SD = 1.35); Effort Expectancy (M = 3.61, SD = 1.39); Facilitating Conditions (M = 3.33, SD = 1.33); Social Influence (M = 3.62, SD = 1.22); and Behavioral Intention (M = 4.50, SD = .73).

Differences between participants on subscales

Table 3 summarizes the calculation of MANOVA to ascertain the combined and individual differences between participants in terms of the dependent variables. First, a difference was found between participants in terms of age when all the dependent variables were combined, F (15, 651.89) = 2.42, Wilks' lambda = .86, p = .002, partial eta squared = .05. At the individual level, a difference was observed in social influence only, F (3, 240) = 3.61, p = .01, partial eta squared = .04. Post hoc comparisons revealed differences between participants aged 26–30 years (M = 3.33, SD = 1.37) and those aged at least 36 years (M = 3.96, SD = .85). Both groups did not differ from those aged 20–25 years (M = 3.46, SD = 1.34) or 31–35 years (M = 3.36, SD = 1.30).

Second, a significant difference was observed between participants in terms of marital status and the combined dependent variables, F (5, 238) = 3.44, Wilks' Lambda = .93, p = .01, partial eta squared = .07. Once again, a difference was observed between participants on social influence only, F (1, 242) = 7.93, p = .01, partial eta squared = .03. The mean scores showed that those who were married (M = 3.83, SD = .97) reported greater social influence than those who were unmarried (M = 3.39, SD = 1.40).

Moreover, a difference was also found between the participants in terms of teaching experience, F (15, 651.89) = 2.56, Wilks' Lambda = .85, p = .001, partial eta squared = .05. A significant difference was reported between participants in facilitating conditions, F (3, 240) = 4.95, p = .002, partial eta squared = .06. Post hoc

Table 3 Differences between participants on sub-scales

	Wilks' Lambda	MAN F	ANOVA F				
			Performance Expectancy	Effort Expectancy	Facilitating Conditions	Social Influence	Behavioral Intention
Place of origin							
M (SD)	.99	.39	.79	.88	1.35	.41	.14
F		.01	.003	.004	.01`	.002	.001
Partial eta squared							
Gender							
F	.99	.36	.35	.01	.22	.49	1.32
Partial eta squared		.01	.001	.001	.001	.002	.01
Age							
F	.86	2.42**	.55	.84	.69	3.61**	2.67
Partial eta squared		.05	.01	.01	.01	.04	.05
Marital status							
F	.93	3.44**	.31	.90	.08	7.93**	4.74
Partial eta squared		.07	.001	.004	.001	.03	.02
Teaching Experience							
F	.85	2.56**	3.45	2.77	4.95**	2.15	3.42
Partial eta squared		.05	.04	.03	.06	.03	.04
Qualification							
F	.92	2.02*	3.10	1.60	2.01	3.65	2.24
Partial eta squared		.04	.03	.01	.02	.03	.02
Teacher Type							
F	.90	1.61	.92	.64	1.18	1.57	3.90
Partial eta squared		.03	.01	.01	.02	.02	.05
School type							
F	.96	1.96	1.16	.07	.001	3.87	5.64
Partial eta squared		.04	.01	.001	.001	.02	.02
School location							
F	.88	3.16**	9.54**	3.83	6.15**	1.57	.26
Partial eta squared		.06	.07	.03	.05	.01	.002

** $p \leq .001$

comparison via Tukey's HSD test revealed differences between participants who had worked for 6–10 years (M = 2.94, SD = 1.43) and those in two groups: 0–5 years (M = 3.59, SD = 1.28) and at least 16 years (M = 3.63, SD = 1.06). Those who had worked for 11–15 years (M = 2.98, SD = 1.29) did not differ from the remaining groups.

Furthermore, differences in the combined dependent variables, F (10, 474) = 3.16, Wilks' Lambda = .88, p = .001, partial eta squared = .06, were found between the participants in different school locations. Significant individual differences were found between participants in performance expectancy (F [2, 241] = 9.54, p = .001, partial eta squared = .07) and facilitating conditions (F [2, 241] = 6.15, p = .002, partial eta squared = .05). In terms of performance expectancy, post hoc comparison via Tukey's

HSD test revealed differences between participants from Al Dhafra (M = 2.26, SD = 1.43) and the two regions Abu Dhabi (M = 3.74, SD = 1.31) and Al Ain (M = 3.62, SD = 1.28). However, those whose schools are located in Abu Dhabia and Al Ain did not differ from each other. With respect to facilitating conditions, those in Al Dhafra (M = 2.28, SD = 1.60) differed from those whose schools are located in Al Ain (M = 3.34, SD = 1.21) and Abu Dhabi (M = 3.47, SD = 1.35). Teachers in Al Ain did not differ from their counterparts in Abu Dhabi.

Predictors of intentions towards AI

The predictors of intention towards AI usage to support students with LDs were explored via hierarchical regression (see Table 4). In Step 1, four predictors were regressed directly on intentions toward AI usage. Here, the predictors made a 7% significant contribution to the variance in intention towards AI usage, R2 = .07; F (4, 239) = 4.73, p = .001. Only two predictors (Effort Expectancy [beta = − .25, p = .001] and Social Influence [beta = .28, p = .001]) significantly contributed to the variance in intentions toward AI usage.

In Step 2, the demographic variables only made a 6% contribution to the variance in intention towards AI usage, R2 change = .06; F (9, 230) = 1.88, p = .05. The combined predictors and demographic variables contributed 14% of the variance in behavioural intentions, R2 = .14; F (13, 230) = 2.81, p = .001. While none of the demographic variables significantly contributed to behavioural intentions, only effort expectancy (beta = − .26,

Table 4 Predictors of behavioural intentions

	Unst. Beta	S.E	Beta	t	p	Confidence interval	
						Lower	Upper
Step 1							
Performance Expectancy	.03	.04	.06	.71	.48	− .06	.12
Effort Expectancy	− .13	.04	− .25	− 3.27	.001**	− .21	− .05
Facilitating Conditions	.03	.05	.06	.74	.46	− .06	.12
Social Influence	.17	.05	.28	3.70	.001**	.08	.26
Step 2							
Performance Expectancy	.04	.04	.08	.97	.34	− .05	.13
Effort Expectancy	− .13	.04	− .26	− 3.32	.001**	− .21	− .06
Facilitating Conditions	.03	.05	.06	.69	.49	− .06	.12
Social Influence	.19	.05	.32	4.09	.001**	.10	.28
Place of origin	.07	.10	.05	.67	.50	− .13	.27
Gender	− .07	.10	− .05	− .72	.48	− .28	.13
Age	− .02	.06	− .03	− .28	.78	− .14	.11
Marital status	− .18	.12	− .13	− 1.54	.13	− .42	.05
Teaching Experience	− .06	.067	− .10	− 1.09	.28	− .18	.05
Qualification	.05	.07	.05	.73	.47	− .08	.18
Teacher Type	− .04	.04	− .06	− .91	.37	− .13	.05
School type	.14	.10	.09	1.37	.17	− .06	.33
School location	.06	.08	.05	.78	.44	− .09	.21

** $p \leq .001$

$p = .001$) and social influence (beta = .32, $p = .001$) significantly contributed to the variance in behavioural intentions.

Following this, path analysis was computed to ascertain/confirm the predictors of intentions. The goodness-of-fit indices were acceptable: chi-square = 3.16 (CMIN = 448.06, df = 142), CFI = .95, TLI = .94, RMSEA = .09 and SRMR = .04. The predictors contributed 9% of the variance in behaviour intentions (R2 = .09). Like in the multiple regression, effort expectancy (b = − .29, p = .001) and social influence (b = .31, $p = .001$) contributed significantly to the variance in behavioural intentions (see Fig. 3).

Discussion

The current study was guided by the UTAUT to understand the intentions of teachers towards adopting AI to support students with LDs. In the UAE and similar contexts, although there are legal instruments safeguarding the education of children with LDs in regular classrooms (Alzamil, 2021; Massouti et al., 2023, 2024b), teachers struggle to support students with LDs (Khasawneh, 2021; Munawarah & Ilmiani, 2024; Serry et al., 2022). However, AI is emerging as a useful tool that could complement the efforts of teachers, who are in search of strategies to enhance the learning of students with LDs. Three research questions were addressed in this study: a) level of intention of teachers;

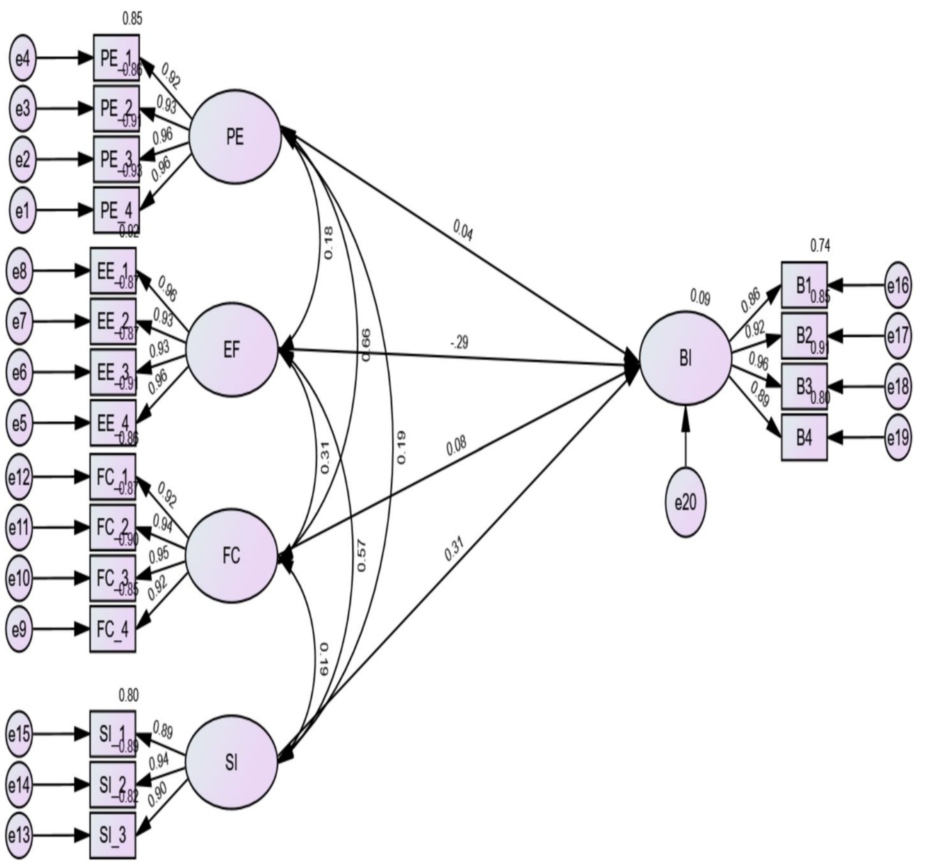

Fig. 3 Path analysis showing predictors of behavioural intentions *Note:* PE, Performance Expectancy; EF, Effort Expectancy; FC, Facilitating Conditions; SI, Social Influence; BI, Behavioral Intention

b) differences in intentions between teachers; and c) predictors of intention towards supporting students with LDs. On the basis of the theoretical framework guiding the study, the predictive power of four variables (effort expectancy, social influence, facilitating conditions and performance expectancy) are combined to explain teachers' intentions to support students with LDs.

Research question one sought to assess the level of teachers' intention towards using AI to teach students with LDs in classrooms. According to Ajzen, one's intention reflects what would do in reality. In this study, it was surmised that in the event that teachers rated themselves highly on each of the tenets of intentions, there is an indication that they would deploy AI in their classrooms to teach students with LDs. However, the findings revealed teachers' neutrality or uncertainty in the use of AI to support the teaching of students with AI. This finding is inconsistent with those of previous studies reporting positive attitudes of teachers towards using AI to facilitate the teaching of students (Al Darayseh, 2023; Galindo-Domínguez et al., 2024; Niu et al., 2022). Two factors could explain this study trend. First, there is a long-standing challenge faced by teachers toward teaching children with LDs in regular classrooms (Crispel & Kasperski, 2021; Damianidou & Phtiaka, 2018; Inês et al., 2022). It is possible that teachers are not trained on which AI tool to integrate into their lessons to facilitate the learning of students with LDs. However, there is evidence that AI could be beneficial in improving the academic skills of students with LDs (Barua et al., 2022; Bressane et al., 2024; Cibrian et al., 2022). Teacher educators in the UAE could take steps toward upskilling teachers in usage and effective ways to integrate AI into lessons. Another possible reason is the absence of an AI policy framework for adoption in schools. Policies directly impact teaching and school practices (Abedi, 2024; Khaleel et al., 2021; Opoku et al., 2021). In the absence of a cohesive policy, teachers are not obligated to integrate or search for tools that could be utilized to support all students, including those with LDs.

The second research goal was to examine differences in intentions among the study participants. Previous studies have often assessed the differences between teachers in the intention to integrate AI in the teaching of students (AN et al., 2023; Ma & Lei, 2024; Roy et al., 2022). This is in line with Ajzen's proposition that background variables of individuals, such as teachers, could provide additional insight into the intention towards a given phenomenon. Hypothesis II was partially supported, as differences were noted between teachers in terms of school location, age and teaching experience. Specifically, differences were noted between teachers in terms of school location on two subscales: performance expectancy and facilitating conditions. Teachers working in Al Dhafra, a comparatively underresourced area relative to Abu Dhabi and Al Ain, reported reduced access to supportive infrastructure and enabling conditions. This finding is in line with those of previous studies in other contexts, such as Nigeria and Bangladesh, which also revealed that even when teachers hold positive attitudes toward technology, the absence of institutional support can stall meaningful engagement (Adigun et al., 2025; Rana et al., 2024). Conversely, the findings of this study are inconsistent with those of other studies (such as Benibo, 2025), reporting rural teachers' strong awareness of AI in education and their readiness to integrate AI tools into their pedagogical practices, notwithstanding the poor facilitating conditions. It is evident that teachers in Al Dhafra perceived AI integration in lessons as daunting and may not have the resources in schools to enable them to adopt AI to teach. However, even across the two other areas, there is more room for improvement, as teachers were unsure about adopting AI in their classrooms. These patterns reinforce the importance of designing infrastructure and policies that are tailored to the needs of specific educational environments, especially in areas that are often overlooked or underserved.

An interesting trend was observed between participants of different ages. Specifically, teachers who had taught for at least 36 years were more likely to be influenced by social pressure to adopt AI than were those who were between the ages of 26 and 30 years. This finding disagrees with earlier studies that reported no influence of age on the behavioural intentions of teachers towards the use of AI to support students (Al-Amri & Al-Abdullatif, 2024; Gupta, 2024). This finding could be true in the sense that relatively young teachers are usually trying to fit themselves in the profession. In some cases, they are unsure about practices in schools as well as how they are expected to teach. In the literature, it has been widely reported that teachers leave the profession if they are not given the required guidelines to induce them in the school environment (Amitai & Van Houtte, 2022; Heffernan et al., 2022; Ibrahim & Aljneibi, 2022; Murdock, 2022). It could be argued that older teachers could be aware of the school culture and thus follow instructions from their superiors or colleagues. It is essential for school leaders to develop induction programs for young teachers that consider the integration of AI to promote teaching and learning activities.

Research question three sought to understand the predictors of teachers' intention towards the implementation of inclusive education. The UTAUT argues that four factors (social influence, effort expectancy, facilitating conditions and performance expectancy) could affect teachers' behavioral intentions toward using AI to support the learning of students (Abbad, 2021; An et al., 2023; Yakubu et al., 2025). In relation to Hypothesis I, we proposed that the four variables would be combined to predict the behavioural intentions of teachers. However, such a proposition was partially supported, as only two variables (social influence and effort expectancy) had a significant effect on the variance in behavioural intentions. Indeed, social influence made a more significant contribution to the variance in behavioural intentions; for every unit of increase in social influence, behavioural intentions towards AI adoption increased by 32%. While these findings are consistent with those of previous studies that reported social influence as a predictor of behavioural intentions (Gupta, 2024; Rana et al., 2024; Xu et al., 2024; Yakubu et al., 2025; Zaim et al., 2024), they are inconsistent with those of other studies that reported otherwise ((Cabero-Almenara et al., 2024). Social influence refers to significant others, such as colleagues and principals, who can influence participants to adopt AI in their classrooms (Davis, 1989). The trend identified in this study could be related to current practices in schools in the UAE. Specifically, more than 70% of teachers in both public and private schools are expatriates working in schools in the UAE (Loyd et al., 2024). Expatriating teachers work mainly on contracts, as their continuous engagement is dependent on positive annual evaluations. In the event of pressure from immediate-line managers such as school leaders, they are inclined to adopt AI in their teaching to support the learning of students with LDs. In such an environment, teachers may be especially sensitive to institutional expectations, particularly when the adoption of new technologies is perceived as being endorsed by leadership. In the event that policymakers are developing AI educational policies, the role of leaders and training should be prioritized for the effective implementation of such policies in schools.

The direction of the effect of effort expectancy on the variance in behavioural intentions was unexpected. In this study, the results showed that for every unit increase in effort expectancy, teachers' intention toward AI usage decreased by 26%. This finding is inconsistent with those of previous studies reporting positive effects of effort expectancy on the intention of teachers to adopt AI in their classroom (Cabero-Almenara et al., 2024; Chai et al., 2021; Gupta, 2024). However, the findings of this study are consistent with those of previous studies reporting positive effects of effort expectancy on teachers' intention to use AI to teach students generally (Rana et al., 2024; Yakubu et al., 2025). Effort expectancy refers to the ease with which an individual can utilize AI to support teaching and learning activities (Davis, 1989). This suggests that the more difficult teachers perceive AI integration to be, the less likely they are to use it—an outcome that aligns with previous studies (Cabero-Almenara et al., 2024; Chai et al., 2021; Gupta, 2024) but diverges in direction from those in Indonesia and China, where ease of use was less critical owing to prior digital fluency (Xu et al., 2024; Zaim et al., 2024). This finding could be attributed to the limited awareness of teacher training in the use of AI to support the teaching of students with LDs. Teachers currently working in schools (both in the UAE and beyond) do not receive adequate training in the integration of AI to teach students with LDs (McMahon & Firestone, 2024; Zraydi, 2025). In view of this, teachers may not know appropriate tools that they could adopt to teach students with LDs. It is fair to argue that they may be unaware of AI tools specifically developed to teach students with LDs. Therefore, there is a need for teacher educators to design courses in AI usage to teach students with LDs. This has the potential to help teachers acquire the necessary competencies to teach students with LDs in their classrooms.

In contrast to global trends, the current study revealed that performance expectancy—teachers' belief that AI enhances their teaching—did not significantly predict behavioral intention. This result contrasts with prior research across diverse contexts (e.g., Ghana, China, India), where performance expectancy consistently emerged as the most influential predictor of AI adoption (Acquah et al., 2024; AN et al., 2023; Chai et al., 2021; Nikolic et al., 2024; Rana et al., 2024; Xu et al., 2024; Yakubu et al., 2025; Zaim et al., 2024). This study's findings, however, are in agreement with those of other studies that reported a lack of contribution of performance expectancy to the variance in the behavioural intentions of teachers (Chatterjee & Bhattacharjee, 2020). One possible explanation is that teachers in the UAE, particularly those working with students with LDs, may lack direct exposure to or training in AI tools that clearly demonstrate instructional value. Without contextualized examples of how AI can support inclusive education, teachers may not yet perceive its utility—highlighting the urgent need for professional development programs and practice-based AI showcases.

Limitations and directions for future research

While this study offers useful findings, there are several important limitations that should be acknowledged. First, the R square showed a weak level of predictive ability for the endogenous variables in the model. However, Primbs et al. (2023) argued that small effect sizes do not invalidate the study. However, such studies contribute to our knowledge and offer opportunities for further research on a given phenomenon. Since this is the first time that the intention of teachers towards using AI to support students with LDs has been studied, this study has provided snapshots of experience. Additionally, the RMSEA was not within the acceptable range (.03–.08). However, as an absolute fit index, it was complemented by TLI and SRMR, which reached an acceptable level.

Second, the study used a cross-sectional design in which data were collected from participants at a given time. This means that it only shows their thoughts and intentions at a point in time. It does not show how their views or actions might change over time. Future studies could use a longitudinal design to ascertain whether teachers' behavioural intentions change over time. Furthermore, the study is a self-report of AI behaviour as rated by teachers. This is based on teachers' own descriptions of their knowledge and practices. In such cases, responses can sometimes lean toward what teachers believe they should say rather than what they actually do. This could unintentionally present a more optimistic picture than what occurs in the classroom. Nevertheless, future studies could use a qualitative design to gain in-depth insight into the experiences of teachers in regard to the integration of AI in the teaching of students with LDs.

Moreover, the participants all worked in three regions of the Abu Dhabi Emirate—Abu Dhabi city, Al Ain, and Al Dhafra. While this provided a mix of perspectives from public and private schools, the findings may not fully apply to other Emirates or school settings in the UAE. The scope was somewhat limited geographically, which affects how the results can be broadly interpreted. Future studies could be extended to other parts of the country to compare the findings to what has been reported here. In addition, the study did not assess their actual use of AI tools in practice. This leaves a gap between what educators say they are ready to do and what is truly happening in their classrooms. Future studies could use an observational design to ascertain how teachers deploy AI in their classrooms to support students with LDs.

Conclusion and implications for practice

This study set out to explore how teachers in the UAE perceive the integration of AI to support students with LDs—a topic that has received little attention in non-Western contexts. Drawing on the UTAUT framework, the research revealed that social influence and effort expectancy were the only significant predictors of intention, whereas performance expectancy, which is commonly found to be a strong driver in other regions, did not hold explanatory power here. The instrument used for data collection was subjected to rigour validation, which enhances the credibility of the results reported in this study. For instance, only social influence and effort expectancy predicted the behavioural intentions of teachers. Moreover, the mean scores revealed the neutrality of teachers towards AI usage with demographic variables such as age, teaching experience, marital status and school location, providing additional explanations for the intentions of teachers. While these findings are promising, the lack of association between some demographics and intentions lends some to further research in the current study context. For example, demographic variables such as gender, the educational qualifications of teachers, teacher type, school type and the place of origin of teachers were not associated with teachers' intentions to use technology to assist students with LD in classrooms.

These results suggest that while the policy and discourse around AI in education may be evolving, teachers may still feel uncertain about its classroom value—particularly in regard to working with students who have diverse needs. The findings of this study could have implications for policymaking and teaching practices. First, there is a need for ongoing training in ways through which teachers can integrate AI in their classrooms. Specifically, teachers need regular, focused training that can help them build the capacity to integrate the AI and pedagogical competence required to support students with LDs. Schools and educators could offer hands-on, practical training that shows teachers how AI tools can be embedded into lesson planning, differentiation, and assessment—especially for students with LDs. Educators could develop teacher training and professional development models that offer opportunities for teachers to access practical AI training in the context of teaching students with LDs.

Second, policymakers could invest in diverse AI tools in schools. Educators could engage teachers in deliberate on AI tools, which could be appropriate for the teaching of students with LDs. National dialogue could be hosted in different locations to develop a comprehensive picture of AI tools that could enhance the learning of students with LDs. This has the potential to facilitate AI access to teachers in their effort to offer equitable access to education to all. This should be accompanied by technical support in schools for teachers. Once AI tools are made available in schools, qualified information technology teachers are needed to offer practical guidance, especially beginning or young teachers, who may have difficulty manipulating devices/platforms.

Third, there is a need for educators to design a clear AI policy to guide practices in schools. The new UAE education policies could provide clearer guidance on how AI can be used in inclusive education. A bottom-up approach to policy could be considered by policymakers. For example, national dialogue involving educators, students, parents and teachers could meet to discuss AI policies that could be designed in the UAE to enhance teaching and learning. Moreover, schools could develop an induction programme that encompasses AI usage for young teachers. For example, experienced and AI competent teachers could be tasked with mentoring beginning teachers. This would enhance the transition of beginning teachers to the profession as well as develop knowledge about tools that could complement their pedagogical teaching skills. Moreover, schools should invest in building peer-led communities of practice where teachers can share experiences, troubleshoot challenges, and learn collaboratively. Since social influence has proven to be a strong predictor, this type of support network may be critical to meaningful implementation. Teachers who are very competent in AI usage could organize professional development, simulating and guiding their peers in relation to ways in which AI could be used to enhance the teaching of students with LDs.

The current study is novel, as this is the first attempt to study the intention of teachers towards using AI to support students with LDs in a nonwestern context. One of the key contributions of this study is that it introduces a context-sensitive lens to AI adoption. While much of the literature focuses on Western or higher education contexts, this study speaks directly to teachers in mainstream K-12 classrooms in the

Gulf region, offering insights that can inform both policy and future research. The scale developed and tested in this work also provides a validated tool for assessing AI readiness in similar environments—making it useful not only in the UAE but also in comparable educational systems striving for inclusive innovation.

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Data availability
The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval
This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Ethics Committee at United Arab Emirates University (ERSC_2025_5933). All the authors signed an informed consent before participating in this study.

Consent to participate
Informed consent was obtained from all teachers who took part in this study. Also, written informed consent was obtained from the parent.

Competing interest
The authors have nothing to declare.

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