IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Perceived effectiveness of artificial intelligent for special-needs students in Saudi Arabian primary schools: A model study

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Abstract

This study explores the perceived effectiveness of artificial intelligence (AI) for special-needs students in primary schools in Saudi Arabia. The main objective is to uncover the key factors that influence teachers' willingness to accept and use AI technologies in their classrooms. Using the Technology Acceptance Model (TAM), the study examines how perceived ease of use and perceived usefulness shape teachers' attitudes and intentions to adopt AI tools. Data were collected through a structured questionnaire filled out by primary school teachers and analyzed using Smart PLS 4 to identify key factors influencing their acceptance of AI. The study reveals that teachers are more likely to adopt AI tools when they perceive them as easy to use and genuinely beneficial for their students. Perceived usefulness, in particular, emerged as the most influential factor in driving teachers' acceptance of AI for special-needs education. The findings highlight the importance of addressing teachers' perceptions and concerns about AI to ensure its successful integration into classrooms. Teachers are more open to using AI when they realize its value and find it accessible, underscoring the need for user-friendly and impactful AI solutions. This study offers actionable insights for policymakers and educators on how AI can be effectively introduced into primary education, especially for special-needs students. Key recommendations include providing targeted training programs, offering continuous support, and addressing teachers' concerns to foster confidence and competence in using AI technologies.

Keywords: Artificial intelligence, Primary schools, Saudi Arabia, Special needs education, Technology acceptance model.

DOI: 10.53894/ijirss.v8i2.5255
Funding: This work was supported through the Annual Funding track by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia (Number KFU250544).
History: Received: 27 January 2025 **/ Revised:** 28 February 2025 **/ Accepted:** 6 March 2025 **/ Published:** 10 March 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

The integration of technology into education has significantly transformed traditional teaching approaches, particularly in catering to the diverse needs of students. In Saudi Arabia, the primary education system plays a significant role in shaping the academic and cognitive development of young learners. However, addressing the educational needs of students with special needs poses a unique set of challenges. Despite efforts to enhance inclusivity, there remains a pressing need for innovative solutions tailored to the specific needs of these students [1].

Saudi Arabia boasts a robust primary education system, characterized by extensive government investment and a commitment to providing quality education for all. The Ministry of Education oversees the primary education sector, ensuring adherence to national standards and curriculum frameworks. The primary school curriculum encompasses a wide range of subjects aimed at fostering holistic development and preparing students for future academic pursuits. Despite these initiatives, certain segments of the student population, particularly those with special needs, encounter barriers to accessing and engaging with educational materials effectively [2].

Special-needs education in Saudi Arabia has undergone significant advancements in recent years, driven by an increasing recognition of the importance of inclusive education [3]. The government has implemented various policies and programs to facilitate the integration of students with diverse learning requirements into mainstream educational settings. Similarly, partnerships with international organizations and the adoption of best practices have contributed to improving the quality and accessibility of special education services across the country. Despite these efforts, there remains a need for tailored interventions that address the unique learning styles and challenges faced by students with special needs, particularly in primary school settings [4].

Recognizing the complex and evolving nature of special-needs education, there is a growing imperative to harness the potential of technology to enhance personalized learning experiences for students with diverse abilities [5, 6]. In this context, utilizing artificial intelligence (AI) holds immense promise for enhancing the educational outcomes of students with special needs in primary schools. By leveraging AI and machine learning techniques, it can dynamically adjust content delivery, pacing, and instructional strategies to suit individual learning preferences and abilities [7-9]. However, the successful implementation of AI relies not only on its technological capabilities but also on its acceptance and perceived usefulness among stakeholders, including educators [10, 11].

Research in the fields of technology acceptance and educational psychology has established theoretical frameworks to comprehend how individuals perceive and adopt new technologies [12-14]. Models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) provide credible insights into the factors influencing the adoption and utilization of educational technologies, including AI [15, 16]. By applying these models within the context of special-needs education in Saudi Arabian primary schools, researchers can gain a nuanced understanding of the perceived effectiveness of AI and its potential impact on student learning outcomes.

In light of the above, this study attempts to contribute to the development of literature on educational technology and inclusive education by employing a modeling approach to investigate the understandings of stakeholders regarding the use of adaptive learning AI for special-needs students in Saudi Arabian primary schools. Through a quantitative survey, the research seeks to elucidate the factors that influence the perceived usefulness of adaptive learning AI, including ease of use, perceived benefits, attitudes toward technology, and contextual considerations unique to the Saudi Arabian educational landscape.

2. Literature Review

Recent advancements in artificial intelligence (AI) have opened up new vistas of possibility in addressing the multifaceted challenges faced by individuals with special needs [17]. Marino, et al. [18] discuss the potential disruption of AI in special education practices. The authors provide a brief history of AI's evolution and focus on its use in writing software applications for special education. They draw comparisons with traditional software and discuss ethical considerations, implementation, and the training of future special education teachers. The study outlines the potential impact of AI on special education technology, offering a platform for further scholarly investigation.

Across various disabilities, studies have showcased the transformative potential of AI applications, offering tailored solutions to enhance accessibility, foster independence, and promote inclusive participation. Delving into the realm of cognitive support, Mohammad Abedrabbu Alkhawaldeh [19] explored the efficacy of AI in bolstering mathematical skills among students grappling with learning disabilities. Through personalized instruction and adaptive feedback mechanisms, the cognitive tutors demonstrated remarkable effectiveness in enhancing problem-solving abilities and mathematical fluency, underscoring their potential as powerful educational tools.

Similarly, Gkeka, et al. [20] discuss an AI-driven system designed to aid individuals with language disorders, enabling real-time speech-to-text conversion. This innovation breaks down communication barriers and enriches social and academic experiences. Additionally, artificial techniques, including AI, robot technology, and serious games, support learning and teaching for language disorders, enhancing educational processes and social skills, especially for students with language impairments.

Moreover, AI technologies have revolutionized support mechanisms for individuals with visual impairments, offering innovative solutions to enhance mobility and environmental engagement. Mina, et al. [21] explores the use of AI virtual assistance to enhance education for visually impaired learners, focusing on their challenges, adaptability, and curriculum enrichment. The study reveals five key themes, including barriers in learning, the importance of AI virtual assistants, and achieving proficiency through technology. Despite the challenges, AI assistance has enabled visually impaired learners to excel academically. The study suggests improvements in teaching visually impaired students in secondary schools.

In a complementary endeavor, Căilean, et al. [22] unveiled the potential of AI-driven assistive devices, exemplified by smart glasses equipped with object detection algorithms, to enhance spatial awareness and obstacle detection for individuals with blindness. Through real-time environmental feedback and auditory cues, the smart glasses augmented users' perception of their surroundings, enabling them to navigate complex environments with ease and confidence. This transformative technology not only enhanced safety but also promoted greater autonomy and inclusion in diverse social and professional contexts. These advancements, coupled with the introduction of a novel wearable solution utilizing Visible Light Communications (VLC) technology discreetly integrated into a smart backpack, represent significant strides in assistive technology for visually impaired individuals. Experimental evaluations of both solutions have demonstrated their effectiveness in providing personalized assistance and enabling safer navigation, marking substantial progress in this critical area.

AI-powered applications have been developed to cater to a diverse range of disabilities, such as autism spectrum disorder (ASD), dyslexia, and cerebral palsy. One such application involves the integration of AI-powered social robots as interactive companions and therapeutic aids for individuals with ASD. This approach leverages natural language processing (NLP) algorithms to facilitate social skills development and emotional regulation. The social robots provide personalized interventions and interactive dialogue, which help individuals in navigating social nuances and promoting social inclusion and emotional well-being. The study conducted by Ezra Tsur and Elkana [23] suggests that such AI-powered social robots can foster meaningful social interactions and aid in the development of social skills, thereby promoting emotional well-being and social inclusion.

Sharma, et al. [24] highlights the potential impact of Artificial Intelligence (AI) on special education. Specifically, AI has the potential ability to transform the way teachers interact with students with special-needs, making teaching practices more inclusive and accessible. The analysis emphasizes the positive effects of AI on both students and teachers, as it can personalize lessons and promote greater student engagement. This, in turn, can lead to enhanced educational outcomes and improved professional experiences for educators. The findings reveal that AI can revolutionize special education and create more equitable and effective learning environments for students with special-needs. However, more studies are required to fully explore and comprehend the potential capabilities, limitations and menace of AI in this context, and to ensure that its implementation is ethical and equitable.

According to Iyer, et al. [25], dyslexia and dysgraphia pose significant challenges to children's literacy skills, impacting academic performance and emotional well-being. While traditional interventions often require costly one-on-one sessions, artificial intelligence (AI) language learning models offer promising solutions. These models provide personalized feedback and instruction in real time, empowering students, educators, and parents to address these learning disabilities effectively. The study advocates for the integration of AI models to support children with dyslexia and dysgraphia, emphasizing their potential to offer more affordable and accessible solutions to these common learning disabilities.

Furthermore, AI technologies have revolutionized support mechanisms for individuals with motor impairments, such as cerebral palsy, offering innovative solutions to enhance mobility and functional independence.

Bertoncelli, et al. [26] analyzed data from 91 teenagers with cerebral palsy to develop a machine learning model that can identify factors associated with intellectual disability. The findings show that poor manual abilities, gross motor function, and specific types of epilepsy were strongly linked to profound intellectual disability. The developed model demonstrated a high potential to accurately identify individuals at high risk of severe intellectual disability. These results highlight the importance of addressing intellectual disability in teenagers with cerebral palsy.

In another endeavor, Osman, et al. [27] introduced AI-driven prosthetic limbs equipped with sensor arrays and adaptive control algorithms, offering individuals with limb differences and upper-extremity amputations enhanced dexterity and functionality. Through intuitive control interfaces and predictive algorithms, the prosthetic limbs mimicked natural movements and adapted to users' needs, enabling individuals to perform a wide range of daily tasks with precision and ease.

Empirical research has provided compelling evidence of the tangible benefits of AI applications for individuals with special needs, substantiating their practical utility through controlled experiments and field trials. For example, Yang, et al. [28] introduce a conceptual framework for an AI-driven virtual tutor system designed to tackle the substantial challenges of student learning difficulties through psychometric assessments. This framework incorporates validated psychometric scales to evaluate essential learning dimensions, including cognitive abilities, learning styles, and academic skills. These assessments are intended to offer a thorough understanding of each student's distinct learning profile, guiding specific interventions within the adaptive tutoring system. To identify latent patterns, autoencoders are employed for generating student profile vectors, defining state and action spaces to represent desired combinations of engagement modalities. This framework also utilizes advanced Bayesian and hierarchical models to continuously monitor student performance across various psychometric constructs. The proposed system leverages AI, visual generation models, and psychometric assessments to deliver personalized instruction and support, tailored to meet the unique learning characteristics and needs of each student. This approach can mitigate the adverse effects of under-accommodation of special needs and improve students' academic performance and long-term educational outcomes.

Similarly, Bressane, et al. [29] present a cutting-edge Decision Support System (DSS) that leverages artificial intelligence (AI) tools to revolutionize educational methods. The study employs an Artificial Neural Network (ANN) to analyze empirical data, identifying key features and patterns that link study strategies, learning disabilities, and academic performance. Additionally, the researchers utilize a fuzzy-based AI system to generate tailored recommendations for effective educational interventions based on these insights. The study highlights the critical role of study strategies in mitigating the negative impact of learning disabilities on academic outcomes. The proposed AI framework empowers educators to personalize educational approaches by aligning them with the unique cognitive profiles of students. By implementing these personalized interventions, the study emphasizes the potential for significantly improved academic outcomes and greater inclusivity within the learning environment. This innovative approach underscores the transformative power of AI in education, offering a pathway to more effective and equitable learning experiences for all students.

The adoption and utilization of educational technologies, such as adaptive learning AI, are often guided by theoretical frameworks that elucidate how individuals perceive and embrace new technologies. The Technology Acceptance Model (TAM) suggests that perceived usefulness and ease of use are critical determinants of technology acceptance, positing that users are more likely to adopt a technology if they find it beneficial and user-friendly. Another extensively applied model, the Unified Theory of Acceptance and Use of Technology (UTAUT), integrates several factors to provide a comprehensive understanding of technology adoption behavior. These factors include performance expectancy, effort expectancy, social influence, and facilitating conditions, which collectively explain how individuals decide to embrace new technologies. Together, these frameworks provide a robust foundation for understanding and predicting technology adoption, thereby guiding the development and implementation of effective digital learning tools in educational settings [30, 31].

Several studies have explored the factors influencing the acceptance and use of adaptive learning AI in educational environments. Cai, et al. [32] focused on learner attitudes towards ChatGPT-assisted language learning while also addressing potential risks related to its misuse. Utilizing a mixed-methods approach that combined structural equation modeling with interviews, the study examined various factors within the extended three-tier technology use model. The findings reveal that elements such as the quality of information systems and hedonic motivation play a crucial role in shaping performance expectancy and perceived satisfaction in ChatGPT-assisted language learning. Notably, the study identifies behavioral intention as a stronger predictor of learning effectiveness than either perceived satisfaction or performance expectancy. It also highlights the mediating roles of behavioral intention and performance expectancy between other variables. This research offers valuable insights for both practice and future studies, stressing the importance for developers to enhance hedonic motivation and information services in ChatGPT. Additionally, it encourages further exploration of the factors that shape learner attitudes towards ChatGPT-assisted language learning.

Binyamin [33] explored the factors influencing students' use of Learning Management Systems (LMS) in higher education, with a particular focus on the recent introduction of LMS in Saudi Arabia. The study expanded the Technology Acceptance Model (TAM) and existing literature to develop and test a theoretical framework. Through online surveys distributed to 2,000 students across three public universities, the study analyzed responses from 833 participants. Using partial least squares structural equation modeling (PLS-SEM), the analysis identified key factors driving LMS usage, revealed variations in acceptance based on demographic characteristics, and examined how these demographics moderated the proposed relationships. The findings provide valuable insights for scholars, university administrators, and e-learning developers aiming to enhance student LMS usage, especially in regions where adoption has been limited.

Rahmi, et al. [34] conducted an in-depth analysis of 203 studies on e-learning and user acceptance, identifying key factors that shape users' intentions to engage with e-learning systems. The study introduces an enhanced Technology Acceptance Model (TAM) framework, highlighting variables such as Self-Efficacy, Subjective Norm, Interaction, Enjoyment, Anxiety, and Compatibility as crucial influences on users' perceptions of usefulness and ease of use. Additionally, the study presents the Acceptance and Satisfaction Model for E-Learning (ASME), which clarifies the complex relationship between User Satisfaction and the original TAM variables. These findings provide valuable insights for enhancing user engagement and satisfaction in e-learning environments.

Research shows that the perceived effectiveness of adaptive learning AI is shaped by various factors, such as perceived usefulness, ease of use, attitudes toward technology, and contextual elements. Sharma, et al. [35] explored the integration of AI in higher education, focusing on the benefits and challenges within Indian universities. The study gathered data from students, faculty, and management staff to examine the factors influencing AI acceptance and adoption. The findings revealed significant relationships between AI self-efficacy, behavioral intention to adopt AI, perceived usefulness, perceived effectiveness, organizational support, and perceived risk. These insights offer valuable guidance for strategic planning and decision-making in the implementation of AI in higher education.

Kouider [36] explored the factors influencing Algerian EFL teachers' decisions to integrate technology into their teaching practices. The research utilized an adapted version of the Unified Theory of Acceptance and Use of Technology (UTAUT) and employed a mixed-methods sequential explanatory design. Focusing on the Department of English at Hassiba Benbouali University of Chlef, the study examined the impact of various factors on teachers' intentions and actual use of technology in EFL classrooms. The findings indicate that teachers' attitudes toward technology positively influence their intention to use it, while behavioral intention and facilitating conditions significantly determine the actual usage of technology. Additionally, gender, age, and teaching experience were found to moderate the relationship between key psychological factors and behavioral intentions, offering valuable insights into the complex dynamics that shape technology acceptance and use among Algerian EFL teachers.

Alkandari [37] investigated the factors influencing students' acceptance of e-learning at Kuwait University through the lens of the Technology Acceptance Model (TAM1). Analyzing data from 336 undergraduates, the study identified perceived ease of use and perceived usefulness as pivotal in shaping students' attitudes toward Virtual Learning Environments (VLEs). Of these, perceived usefulness emerged as the more significant predictor, strongly influencing both attitudes and intentions to use VLEs. Additionally, external factors such as personal innovativeness, instructor characteristics, course interactivity, and content quality positively impacted students' perceptions. The study also highlighted that perceived ease of use had a strong effect on perceived usefulness, with self-efficacy playing a crucial role in determining the ease of use of VLEs.

Al-Mamary [38] assessed the applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) and contextual factors in the integration of Learning Management Systems (LMS) within Saudi Arabian universities. The study gathered data from 277 students at the University of Hail through questionnaires and utilized Structural Equation Modeling (SEM) to evaluate the proposed conceptual model. The results revealed that students' intentions to use LMS are significantly shaped by expected effort and social influence, while behavioral intentions and facilitating conditions play a crucial role in determining actual usage behavior. These findings provide valuable insights for university policymakers aiming to implement LMS in Saudi Arabian educational institutions.

In the context of Saudi Arabian, there are unique factors such as awareness, cultural, social, policy and institutional factors that may influence the acceptance and effectiveness of adaptive learning

Al Shehri, et al. [39] conducted an investigation into the acceptance of assistive technology (AT) among visually impaired students within Saudi universities, expanding the Unified Theory of Acceptance and Use of Technology (UTAUT) to include context-specific factors. Utilizing Structural Equation Modeling (SEM) to analyze survey data, the study identified distinctive acceptance factors, which differ from those observed in other contexts, primarily due to limited awareness and cultural sensitivity. Follow-up interviews provided further clarification of these contextual differences. The study offers targeted recommendations for overcoming barriers to AT acceptance and provides critical insights for Saudi government and university administrators to enhance access to assistive technologies for visually impaired students.

Zalah [40] explored e-learning adoption among secondary school teachers in Saudi Arabia's Jazan region. It proposes a revised framework using the UTAUT model, incorporating factors such as experience, attitudes, and anxiety. A survey and interviews revealed that performance, effort, attitudes, and policy positively impact adoption while anxiety has a negative impact. The study emphasizes the importance of overcoming barriers to technology adoption in developing countries.

Sobaih, et al. [41] examined the acceptance and utilization of ChatGPT among 520 students in Saudi Arabian higher education, employing the comprehensive Unified Theory of Acceptance and Use of Technology (UTAUT2) framework. Structural equation modeling results revealed significant direct effects of performance expectancy (PE), social influence (SI), and effort expectancy (EE) on both behavioral intention (BI) and actual ChatGPT usage. Interestingly, the study found that facilitating conditions (FCs) did not have a direct impact on BI or actual use. Additionally, the research identified partial mediation of BI between PE, SI, FC, and actual ChatGPT use, while full mediation was observed between EE and actual usage. These findings carry important implications for academics and institutions in Saudi Arabia and similar contexts, emphasizing the need to prioritize factors like PE, SI, and EE to facilitate the successful adoption and integration of ChatGPT.

The literature reviewed provides valuable insights into the perceived effectiveness of adaptive learning AI for special-needs students in Saudi Arabian primary schools. Drawing upon theoretical frameworks such as TAM and UTAUT, recent studies have identified factors influencing technology acceptance and utilization. Moreover, research highlights the potential of adaptive learning AI to enhance personalized learning experiences and improve student outcomes. However, there is a need for further research to explore the perceived effectiveness of adaptive learning AI for special-needs students in the unique context of Saudi Arabian primary schools.

3. Method

This study uses a quantitative research approach to examine the perceived effectiveness of adaptive learning AI for special-needs students within the context of Saudi Arabian primary schools.

The proposed hypotheses for this study are:

i. Perceived Ease of Use (PEU) has a significant positive effect on Attitude Towards Use (AT) regarding adaptive learning AI in supporting special-needs students in Saudi Arabian primary schools.
ii. Perceived Ease of Use (PEU) has a significant positive effect on Behavioral Intention to Use (BI) adaptive learning AI in supporting special-needs students in Saudi Arabian primary schools.
iii. Perceived Usefulness (PU) has a significant positive effect on Attitude (AT) towards using adaptive learning AI for special-needs students in Saudi Arabian primary schools.
iv. Perceived Usefulness (PU) has a significant positive effect on Behavioral Intention (BI) to use adaptive learning AI for special-needs students in Saudi Arabian primary schools.
v. The attitude (AT) towards use has a significant positive effect on the behavioral intention (BI) to use adaptive learning AI for special-needs students in Saudi Arabian primary schools.

The population of the study comprises 779 teachers of special-needs students in Al-Ahsa Province, Saudi Arabia. A systematic random sampling technique was used to select 350 participants as the sample size of the study to ensure adequate representation of the participants. A structured questionnaire was designed using established scales and constructs from the Technology Acceptance Model (TAM). This questionnaire evaluated teachers' perceptions of AI, focusing on perceived usefulness, ease of use, attitudes toward technology, and behavioral intentions [42]. 350 questionnaires were distributed electronically to participants using online survey platforms through email and WhatsApp applications. Clear instructions and informed consent were provided to ensure compliance with ethical guidelines. Participants were given a specified period to complete the questionnaire, and reminders were sent to enhance response rates. The data collection process lasted approximately two months. 315 questionnaires were received duly completed.

The data analysis included descriptive statistics to summarize participants' demographic information and inferential statistics, such as correlation and regression analyses, to explore relationships between variables and test hypotheses about the perceived effectiveness of adaptive learning AI [43]. The data were analyzed using Smart PLS 4

The questionnaire was validated by 3 experts, pilot tested with a small sample of participants for instrument validity. Additionally, Cronbach's alpha test is run to assess the reliability of the instrument [44].

4. Result

This study examines the perceived effectiveness of Artificial Intelligence (AI) for special-needs students in primary schools in Al-Ahsa Province, Saudi Arabia, applying the Technology Acceptance Model (TAM). Data were gathered from teachers and analyzed with factor analysis using Smart PLS 4, concentrating on constructs such as Attitude Towards Use (AT), Behavioral Intention to Use (BI), Perceived Ease of Use (PEU), and Perceived Usefulness (PU).

4.1. Demographic Information of the Respondents

The results from the descriptive statistics of the participants' demographic information provide a comprehensive overview of respondent composition across three key variables: Age, Gender, and Working Experience. Analysis of the age distribution reveals that the largest segments of respondents fall within the 26-35 and 36-45 age brackets, collectively constituting 83.8% of the total sample. In terms of gender representation, the majority of respondents identify as male, comprising 75.2% of the total sample, while female respondents make up 24.8%. Furthermore, the data indicates that a significant portion of respondents possess more than 10 years of working experience, accounting for 71.4% of the total sample. Notably, a discernible pattern emerges wherein the predominant demographic profile comprises males aged between 26 and 45, who exhibit extensive working experience; see Table 1.

Table 1.
Demographic Information of the respondents

Variable	Values	Frequency	Percent
Age	22-25	3	1.0
	26-35	111	35.2
	36-45	153	48.6
	46-55	48	15.2
	Total	315	100.0
Gender	Male	237	75.2
	Female	78	24.8
	Total	315	100.0
Working Experience	Less than 1 Year	6	1.9
	1 - 5 Years	33	10.5
	6 - 10 Years	51	16.2
	More than 10 Years	225	71.4
	Total	315	100.0

4.2. Descriptive Statistics

The descriptive statistics for the constructs are presented in Table 1. The mean scores for all items were relatively high, indicating a generally positive perception of AI in the context of special-needs education. Notably, items under PU had the highest means, suggesting that teachers perceive AI as useful in enhancing educational outcomes for special-needs students.

Table 2.
Descriptive statistics.

Construct	Item	Mean	Standard Deviation	Kurtosis	Skewness
AT	AT1	3.39	1.09	-0.27	-0.60
	AT2	2.75	1.26	-1.09	0.01
	AT3	2.94	1.06	-0.82	0.11
	AT4	3.76	0.92	0.67	-0.69
	AT5	2.94	1.06	-0.82	0.11
	AT6	3.39	1.09	-0.27	-0.60
BI	BI1	3.50	0.94	0.31	-0.65
	BI2	3.72	0.86	2.16	-1.17
	BI3	3.76	0.88	1.26	-0.87
	BI4	3.75	0.88	1.86	-1.09
	BI5	3.77	0.83	1.90	-0.95
	BI6	3.97	0.80	2.41	-1.08
PEU	PEU1	3.29	0.85	0.28	-0.30
	PEU2	3.28	0.86	0.08	-0.38
	PEU3	3.52	0.79	1.41	-0.77
	PEU4	3.44	0.80	1.55	-0.63
	PEU5	3.63	0.78	2.14	-1.15
	PEU6	3.49	0.75	1.18	-0.68
PU	PU1	3.68	0.68	3.03	-1.11
	PU2	3.84	0.78	3.48	-1.39
	PU3	3.92	0.71	4.19	-1.31
	PU4	3.87	0.78	2.43	-1.08
	PU5	3.78	0.84	1.19	-0.83
	PU6	3.95	0.77	2.92	-1.16

The standard deviations indicate moderate to high variability in responses, suggesting differing levels of acceptance and perception among the teachers. The skewness and kurtosis values for most items fall within acceptable ranges, confirming that the data are approximately normally distributed.

4.3. Construct Reliability and Validity

The analysis of the constructs—Attitude, Behavioral Intention, Perceived Ease of Use, and Perceived Usefulness—reveals high reliability and validity. Cronbach's alpha values for all constructs exceed the acceptable level of 0.7, with Behavioral Intention, Perceived Ease of Use, and Perceived Usefulness demonstrating particularly strong internal consistency (above 0.9). Composite reliability values (rho_a and rho_c) are also well above the 0.7 threshold, confirming the strong internal consistency of the constructs. Additionally, the Average Variance Extracted (AVE) values for all constructs surpass the recommended 0.5, indicating good convergent validity. Specifically, Behavioral Intention has the highest AVE (0.750), followed by Perceived Usefulness (0.719), Perceived Ease of Use (0.684), and Attitude (0.572). These results indicate that the measurement items reliably represent their respective constructs and that the constructs effectively capture the theoretical concepts, making them appropriate for further analysis in the structural model.

Table 3.
Construct reliability.

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Attitude	0.745	0.727	0.838	0.572
Behavioral Intention	0.931	0.941	0.947	0.750
Perceived Ease of Use	0.908	0.923	0.928	0.684
Perceived Usefulness	0.922	0.925	0.939	0.719

4.4. Fornell-Larcker Criterion

The Fornell-Larcker criterion table illustrates the discriminant validity among the constructs: Attitude, Behavioral Intention, Perceived Ease of Use, and Perceived Usefulness. The diagonal values represent the square root of the Average Variance Extracted (AVE) for each construct, which are: Attitude (0.757), Behavioral Intention (0.866), Perceived Ease of Use (0.827), and Perceived Usefulness (0.848). The off-diagonal values indicate the correlations between constructs. The table demonstrates that each construct's square root of AVE exceeds its highest correlation with any other construct, confirming discriminant validity. Specifically, the highest correlation is between Perceived Usefulness and Perceived Ease of Use (0.778), which is lower than the square root of AVE for both constructs. This suggests that the constructs are distinct and that the measurement model exhibits strong discriminant validity.

Table 4.
Fornell-Larcker criterion table.

Fornell-Larcker criterion	Attitude	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness
Attitude	0.757			
Behavioral Intention	0.603	0.866		
Perceived Ease of Use	0.482	0.726	0.827	
Perceived Usefulness	0.490	0.727	0.778	0.848

4.5. Heterotrait-Monotrait Ratio (HTMT)

The Heterotrait-Monotrait Ratio (HTMT) values for the constructs—Behavioral Intention, Attitude, Perceived Ease of Use, and Perceived Usefulness—demonstrate strong discriminant validity. All HTMT values are below the 0.85 threshold, with the highest value being 0.833 for the correlation between Perceived Usefulness and Perceived Ease of Use. Other significant HTMT values include 0.688 for the relationship between Behavioral Intention and Attitude, 0.535 for Perceived Ease of Use and Attitude, and 0.529 for Perceived Usefulness and Attitude. These results confirm that the constructs are distinct from one another, thereby supporting the validity of the measurement model employed in the study.

Table 5.
Heterotrait-Monotrait Ratio (HTMT).

	Heterotrait-monotrait ratio (HTMT)
Behavioral Intention <-> Attitude	0.688
Perceived Ease of Use <-> Attitude	0.535
Perceived Ease of Use <-> Behavioral Intention	0.771
Perceived Usefulness <-> Attitude	0.529
Perceived Usefulness <-> Behavioral Intention	0.775
Perceived Usefulness <-> Perceived Ease of Use	0.833

4.6. Variance Inflation Factors (VIF)

Several relationships in the model were assessed using Variance Inflation Factors (VIF) to gauge multicollinearity. The findings indicate varying degrees of multicollinearity among the variables. Notably, the Attitude to Behavioral Intention link exhibited the lowest VIF at 1.363, indicating minimal multicollinearity. Conversely, connections involving Perceived Ease of Use and Perceived Usefulness with both Attitude and Behavioral Intention showed slightly higher VIF values ranging from 2.533 to 2.649. These results suggest manageable interdependencies among the variables, affirming the model's reliability in predicting behavioral intentions based on perceived ease of use and usefulness.

Table 6.
Variance inflation factors (VIF).

Inner model	VIF
Attitude -> Behavioral Intention	1.363
Perceived Ease of Use -> Attitude	2.533
Perceived Ease of Use -> Behavioral Intention	2.621
Perceived Usefulness -> Attitude	2.533
Perceived Usefulness -> Behavioral Intention	2.649

4.7. Factor loading

The factor loading analysis for four key constructs—Attitude (AT), Behavioral Intention (BI), Perceived Ease of Use (PEU), and Perceived Usefulness (PU)—was conducted using SmartPLS to assess the reliability and validity of the measurement model. The loadings for the Attitude construct ranged from 0.561 to 0.878, with AT1 and AT6 showing strong correlations (0.878), while AT2 (0.658) and AT4 (0.561) exhibited weaker correlations. Notably, AT3 and AT5 were removed due to lower loadings that did not meet the acceptable threshold. For Behavioral Intention, loadings ranged from 0.670 to 0.925, with BI2, BI3, BI4, BI5, and BI6 displaying high loadings above 0.850, indicating strong representation of the construct, while BI1 had a lower loading of 0.670. The Perceived Ease of Use construct had loadings between 0.760 and 0.875, with all items showing good representation of the construct. Similarly, Perceived Usefulness exhibited loadings from 0.777 to 0.890, with all items strongly representing the construct.

Overall, most items demonstrated strong factor loadings, generally exceeding 0.7, which indicates that they are reliable indicators of their respective constructs. Constructs such as Behavioral Intention, Perceived Ease of Use, and Perceived Usefulness showed high reliability and strong correlations among their indicators. However, items within the Attitude construct, particularly AT2 and AT4, may need further examination or refinement to improve their representational accuracy. The factor loading analysis supports the validity of the measurement model used in this study. The high factor loadings across most items confirm their strong correlation with their underlying constructs, providing a solid foundation for further structural model analysis and hypothesis testing. This analysis highlights the reliability of the constructs measured and suggests areas for improvement to enhance the accuracy and effectiveness of the measurement model.

Table 7.
Loading.

	Attitude	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness
AT1	0.878			
AT2	0.658			
AT4	0.561			
AT6	0.878			
BI1		0.670		
BI2		0.905		
BI3		0.895		
BI4		0.921		
BI5		0.925		
BI6		0.851		
PEU1			0.760	
PEU2			0.832	
PEU3			0.864	
PEU4			0.802	
PEU5			0.825	
PEU6			0.875	
PU1				0.777
PU2				0.856
PU3				0.843
PU4				0.857
PU5				0.861
PU6				0.890

4.8. Inner Model Analysis

The inner model revealed the relationships between the constructs. The path coefficients and their significance levels were evaluated to understand the strength and significance of the relationships within the model (Table 4).

4.9. Path Coefficients

The empirical analysis provided strong support for the hypothesized relationships within the model, with all paths showing significant statistical outcomes. Specifically, Attitude significantly predicted Behavioral Intention ($\beta = 0.281$, $p = 0.001$), demonstrating a positive effect. Perceived Ease of Use exhibited significant positive impacts on both Attitude ($\beta = 0.254$, $p < 0.001$) and Behavioral Intention ($\beta = 0.335$, $p < 0.001$), highlighting its essential role in shaping user attitudes and intentions. Similarly, Perceived Usefulness significantly influenced Attitude ($\beta = 0.293$, $p < 0.001$) and Behavioral Intention ($\beta = 0.328$, $p = 0.001$), underscoring its critical impact on behavioral outcomes.

These findings underscore the model's reliability and explanatory power, elucidating key factors driving user behaviors. The results emphasize the paramount importance of perceived ease of use and usefulness in fostering positive attitudes and behavioral intentions. This validation of the model's structure highlights the significance of these constructs as foundational elements in predicting user acceptance and usage intentions, offering valuable insights into the mechanisms underlying user behavior.

Table 8.
Hypothesis report.

Hypothesis	Path	Path coefficients	p value
Attitude -> Behavioral Intention	Positive	0.281	0.001
Perceived Ease of Use -> Attitude	Positive	0.254	0.000
Perceived Ease of Use -> Behavioral Intention	Positive	0.335	0.000
Perceived Usefulness -> Attitude	Positive	0.293	0.000
Perceived Usefulness -> Behavioral Intention	Positive	0.328	0.000

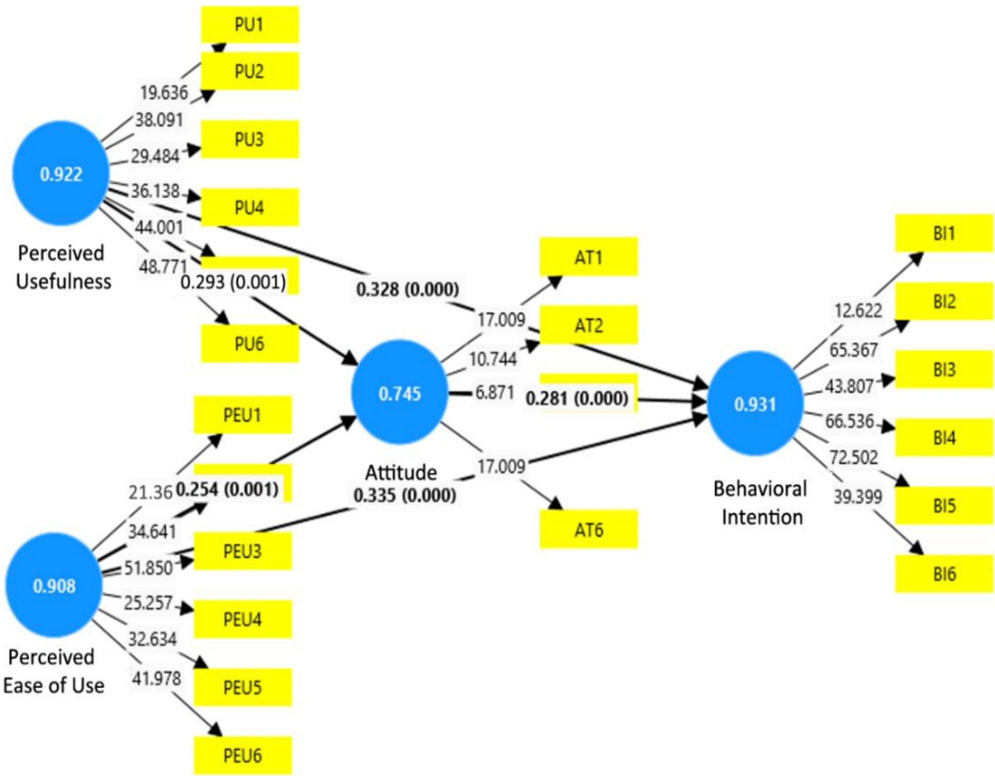

Figure 1.
Path model of teachers' acceptance of AI in special needs education, smart PLS approach

5. Discussion

This study provides valuable insights into how adaptive learning AI is perceived to be effective for special-needs students in primary schools in Saudi Arabia, based on the Technology Acceptance Model (TAM). The findings highlight the crucial impact of perceived ease of use (PEU) and perceived usefulness (PU) on shaping teachers' attitudes (AT) and behavioral intentions (BI) regarding the adoption of AI technologies.

The positive correlations observed between PEU and both AT and BI underscore the importance of user-friendly AI tools. Teachers are more inclined to adopt technologies that they find easy to use, which aligns with established research indicating that simplicity significantly impacts technology acceptance [45, 46]. This finding suggests that when AI tools are intuitive and require minimal effort to learn and use, teachers are more likely to develop positive attitudes towards them and intend to integrate them into their teaching practices. This aligns with Venkatesh and Bala [47] extension of TAM, which integrates additional constructs to understand how external variables influence technology acceptance.

Perceived usefulness also significantly influences teachers' attitudes and behavioral intentions. The strong correlation between PU and both AT and BI indicates that teachers are more inclined to incorporate AI into their teaching practices if they believe it will effectively improve educational outcomes for special-needs students. This finding aligns with previous research emphasizing the role of perceived effectiveness in technology adoption [48]. When teachers see clear benefits from AI, such as personalized learning and enhanced student engagement, their readiness to adopt these technologies increases. This is further supported by studies showing that perceived usefulness is a major predictor of technology adoption [49, 50].

The significant positive relationship between AT and BI demonstrates that a favorable attitude towards AI is a key driver of teachers' intentions to use these technologies. This mediating role of attitude in the acceptance process highlights the need for strategies that not only enhance the perceived ease of use and usefulness of AI tools but also foster positive attitudes among teachers. Creating an environment where teachers feel confident and positive about AI can significantly enhance the likelihood of successful technology integration. This finding aligns with Fishbein and Ajzen [51] Theory of Reasoned Action, which posits that attitudes towards behavior significantly influence behavioral intentions.

The findings of this study are consistent with the broader literature on technology acceptance. The Technology Acceptance Model (TAM) has been extensively validated in various fields, including education, healthcare, and organizational contexts [47]. The continued support for Perceived Ease of Use (PEU) and Perceived Usefulness (PU) in predicting Attitude Towards Use (AT) and Behavioral Intention to Use (BI) highlights the effectiveness of TAM in explaining technology adoption behaviors. Nonetheless, the application of AI in education, especially for special-needs students, introduces significant ethical concerns. Issues such as data privacy, algorithmic bias, and the risk of excessive dependence on technology need to be addressed carefully. It is essential to design and implement AI tools with a focus on students' best interests to ensure their acceptance and effectiveness [52]. Developing ethical frameworks and guidelines will help ensure that AI enhances rather than detracts from the educational experience.

Similarly, the positive impact of PEU on AT and BI emphasizes the importance of providing adequate training and professional development for teachers. Ensuring that teachers have the necessary skills and knowledge to effectively use AI tools can enhance their perceived ease of use and usefulness, ultimately fostering positive attitudes and behavioral intentions. Training programs that focus on practical, hands-on experiences and offer ongoing support can significantly improve AI adoption rates among teachers [53]. This finding suggests that professional development should be an integral component of any AI implementation strategy in education.

6. Practical Implications

The study's findings have several practical implications for policymakers, educators, and technology developers. Developers should focus on creating AI tools that are user-friendly and easy to learn, as a simplified user interface can enhance teachers' perceptions of ease of use, supported by user-centered design principles [54]. Highlighting the tangible benefits of AI for special-needs education through case studies, pilot programs, and success stories can enhance perceptions of usefulness and motivate adoption [55]. Comprehensive training and ongoing support are crucial for successful AI integration, focusing on practical skills and continuous support [56]. Additionally, educational policies should support AI integration by providing necessary resources and infrastructure, ensuring schools have access to the required technology and support [57].

7. Conclusion

The factor analysis conducted with Smart PLS 4 confirmed the relevance of the Technology Acceptance Model (TAM) in analyzing teachers' perceptions of AI for special-needs students in Saudi primary schools. By focusing on ease of use and perceived usefulness, educational stakeholders can create a more supportive environment for integrating AI, thereby enhancing the educational experience for special-needs students. This study offers valuable insights for policymakers, educators, and technology developers looking to utilize AI to improve educational outcomes for these students.

Future research should consider including additional stakeholders, such as students and parents, to provide a more comprehensive understanding of AI acceptance in special-needs education. Additionally, examining the long-term impacts of AI integration and addressing ethical considerations will be essential for ensuring the responsible and effective use of AI in educational settings.

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