

PAPER

Factors Influencing the Educational Technology Integration of Robots by Preservice Special Education Teachers for Students with Autism Spectrum Disorder

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ABSTRACT

This study examines the psychological, social, and professional factors that can influence pre-service special education teachers' (PSETs) intentions to integrate educational robots (EDRs) into teaching students with autism spectrum disorder (ASD). Using structural equation modeling (SEM) and the extended technology acceptance model (TAM), the study examines the roles of perceived usefulness (PU), perceived ease of use (PEOU), attitude toward integration robot (ATIR), robot self-efficacy (RSE), job relevance (JOR), social influence (SI), and robot anxiety (RANX). This study addresses a research gap, as it is, to the best of our knowledge, the first conducted in an Arab context. A quantitative research design was adopted. The researcher gathered responses from 595 PSETs through an online survey platform at three public universities in Jordan. The results revealed that PU was the strongest predictor of positive attitudes toward EDR integration, and ATIR significantly affected behavioral intention. SI and JOR had significant effects on both PU and PEOU. RSE affected PEOU but not PU, while RANX negatively affected PU without significantly impacting PEOU. These findings guide decision-makers and institutions on how to effectively support special education teachers (SETs) in integrating robots into teaching students with ASDs.

KEYWORDS

technology acceptance model (TAM), intention to integrate technology, attitude, robot, preservice teacher, special education, autism, autism spectrum disorder (ASD)

1 INTRODUCTION

Educational robots (EDRs) are pedagogical tools that enhance learning experiences [1]. EDRs offer interactive learning environments that support the development of social and communication skills, which in turn enhance students' academic and behavioral abilities [2]. They are innovative pedagogical technologies that

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help instructors to create appropriate learning environments tailored to the needs of students with autism spectrum disorder (ASD), enhancing their participation in the learning process [2–3]. Because traditional instruction often fails to meet learners' needs, educators have shifted to immersive, game-based technologies [4], and more broadly, technology has been shown to boost student engagement and learning outcomes [5]. Integrating technology in education, such as EDRs, aligns with international standards that highlight the importance of inclusive education for all. For example, the United Nations Convention on the Rights of Persons with Disabilities (CRPD) stresses the right to inclusive education, which can be effectively implemented through assistive technology [6]. Furthermore, the CRPD Committee encourages States Parties to invest in innovative technologies [7]. Integrating technology into education also contributes to achieving the fourth goal of the Sustainable Development Goals (SDGs), which focuses on inclusive, equitable quality education and lifelong learning opportunities for all. Similarly, UNESCO's report [8] on using Information and Communication Technologies (ICTs) in education for persons with disabilities encourages governments and educational institutions to adopt ICTs to enable authentic pedagogical transformation.

The Council for Exceptional Children [9] emphasizes the importance of thoroughly preparing special education teachers (SETs) and ensuring they master the skills and knowledge necessary for safe and effective practice. Therefore, they developed the 2020 Initial K–12 Standards, which highlight the importance of working with K–12 students and require SETs to possess technological skills to meet the fourth standard. Furthermore, the International Society for Technology in Education [10] developed standards for educators that require them to integrate technology into their practice to create high-impact, sustainable, scalable, and equitable learning experiences that accommodate student variability and enhance learning. These standards have been implemented by all U.S. states and many countries around the world. This means that effectively preparing PSETs involves equipping them with the necessary skills, knowledge, and attitudes to integrate technology into education, including innovative digital tools such as robots.

Literature on EDRs for students and children with ASD highlights their beneficial role in supporting rehabilitation, therapy, and education for individuals with ASD [2]. More specifically, EDRs enhance social interaction, communication, and emotional regulation skills [11]. Additionally, they positively affect cognitive abilities, learning disposition, engagement, attention, and focus in young children with ASD [12]. Despite these benefits, there is significant skepticism regarding the use of robots in education and the care of individuals [13]. For instance, studies have found that teachers often hold negative attitudes toward robots [14], even though acceptance and attitude toward EDRs are vital ergonomic constructs affecting the intention to adopt and use such technologies [15]. Moreover, the existing literature provides limited insight into PSETs' perceptions and behaviors regarding the acceptance of integrating technology into their interventions [16]. Therefore, there is an urgent need to conduct research that explores the factors affecting the intention to integrate robots for students with ASD. The present research seeks to fill this void by exploring the key determinants influencing the intention of PSETs to integrate EDRs into their teaching practices for students with autism. An extended technology acceptance model (TAM) was adopted as the conceptual framework to assess external factors—robot anxiety, robot self-efficacy (RSE), job relevance, and social influence—among PSETs at the School of Educational Sciences in a sample of public universities in Jordan. This study bridges the knowledge gap related to understanding the integration of EDRs for students with ASD and the key factors influencing this process.

2 THEORETICAL FOUNDATIONS AND RESEARCH MODEL

The TAM serves as a theoretical foundation for clarifying and exploring factors that impact the technology acceptance and usage intentions [17–19]. It identifies two main constructs—perceived ease of use (PEOU) and perceived usefulness (PU)—affect how system features (i.e., external factors) affect intended use [20]. PU is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” [21], indicating that PU refers to an individual’s belief in the benefits of using a specific system to improve job performance. PEOU is defined as “the degree to which a person believes that using a particular system would be free of effort” [21], referring to the extent an individual believes the system requires minimal effort to use.

Several studies have confirmed that PEOU, PU, and attitudes toward specific systems or technologies are positively related [22–24]. Later, researchers extended and adapted the TAM model by modifying its external factors to better suit the study context [19], [25]. Consequently, TAM has evolved to include additional factors that enhance the acceptance and use of technology tailored to specific fields. In general, researchers have examined several factors that may impact technology acceptance and usage, such as anxiety, self-efficacy, affordability, job relevance, social influence, effort expectancy, performance expectancy, and attitude [25–29]; however, the results of these studies have been inconsistent regarding which factors impact the core TAM constructs. For example, the impact of technological anxiety was supported by some studies [30] but rejected by others [31]. More recent research has confirmed the impact of specific external factors, such as the positive impact of job relevance (JOR) on PU [29], self-efficacy on the intention to use course websites [31], and mobile application self-efficacy on both PEOU and PU in the context of e-learning systems [32].

In the literature on robot acceptance and use in education [33–36], no studies have employed the TAM model to investigate the factors affecting PSETs’ intention to use robots for students with ASD. In light of the above literature and related findings, this study proposes an extended TAM model as its theoretical framework.

2.1 Robot self-efficacy

Self-efficacy is defined as an individual’s belief in their ability to perform a given task [37]. It refers to one’s belief in their ability and the required skills to successfully complete a task [38]. Self-efficacy is related to a person’s actual behavior [39] and has been examined by researchers in various contexts, including general and domain-specific technology use. Specific self-efficacy is considered a key construct that relates to an individual’s intention to adopt and use technology [40]. In the domain of technology, self-efficacy affects perceptions of using technological tools and is referred to as technological self-efficacy—one’s belief in having sufficient ability and skills to manage tasks that require technology [38]. Consequently, RSE refers to an individual’s judgment of their ability and competence to integrate and use robots for specific tasks. In this study, RSE is defined as PSETs’ judgments of their abilities and competencies to integrate and use EDRs in therapeutic and educational practices for students with ASD.

Many previous studies have demonstrated a relationship between technology self-efficacy and actual use of technological tools [41–42]. However, few studies

have examined the mediating role of RSE in relation to PEOU and PU in integrating EDRs within special education, despite its critical role in successful interaction [43]. For example, [44] found that self-efficacy is correlated with PEOU in the context of human-robot cooperation. Similarly, [28] revealed that RSE impacts the PEOU of social robots among early adopters. Further, [41] reported that self-efficacy significantly impacts teachers' positive attitudes toward using technologies in their instructional programs. Also, [42] found that self-efficacy is positively related to a deep learning approach and serves as a mediator between perceived support and university students' use of online learning technologies. Based on these findings, the following hypotheses were set:

H1: PSET's RSE positively impacts their PEOU of EDRs for students with ASD.

H2: PSET's RSE positively impacts their PU of EDRs for students with ASD.

2.2 Social influence

Social influence is defined as “the change in a person's cognition, attitude, or behavior, which has its origin in another person or group” [45]. It has attracted the attention of researchers across various contexts and has been a primary focus in the literature on technology acceptance [46]. SI is considered one of the dominant factors influencing an individual's acceptance of technology [47], such as when a teacher's opinions, behaviors, or decisions are shaped by colleagues who encourage the use of innovative technologies like robots. In this study, SI refers to changes in a PSET's cognition, attitude, or behavior toward integrating EDRs into the education of students with ASD that stem from the influence of another person or group. SI has been studied as an external factor in the extended TAM model across different contexts. For example, [48] found that SI significantly affects the PU of e-learning, while [44] reported that subjective norms—one of the key components of SI—positively impact PU in the use of robots in production systems. In this study, SI is defined as a shift in a preservice special education teacher's thoughts, attitudes, or behaviors—originating from others—that leads to the integration of EDRs for students with ASD. Subjective norms are a key element of SI [49]. However, a study by [28] found that subjective norms did not impact PU in the market context. Meanwhile, [50] emphasized the direct effect of normative beliefs on the acceptance of social robots and their positive effect on PU [51]. Conversely, [48] found that teacher influence did not affect students' PEOU of e-learning and noted the limited research on how SI might influence PEOU and PU in educational technology adoption. In another context, [47] found that SI impacted both PU and PEOU, as well as behavioral intention and actual use of energy technologies. Similarly, [52] found that SI impacted PEOU in the adoption of energy-efficiency smart solutions. These findings underscore the need for recent studies to examine the potential impact of SI on PSETs' PU and PEOU in integrating EDRs, particularly since no studies have yet examined SI in the context of EDR use in special education. Based on this, the following hypotheses were formulated:

H3: PSET's social influences positively impact their PEOU of EDRs for students with ASD.

H4: PSET's social influences positively impact their PU of EDRs for students with ASD.

2.3 Robot anxiety

An individual might hold negative views toward information technologies such as robots, computers, or the internet due to trait or state anxiety [28]. Technology anxiety is defined as the negative emotion associated with using technology [53]. It refers to the tension that arises from an individual's expectation of negative outcomes when using technology, stemming from experiential, behavioral, and physiological factors [53]. Robot anxiety (RANX) is defined as a person's "pre-existing" feeling of fear caused by uncertainty about the future and concerns or challenges faced when using robots [54–55]. According to [28], RANX involves negative emotions, tension, or discomfort experienced when using or thinking about robots. Previous studies have demonstrated the impact of anxiety on technology acceptance. Specifically, anxiety has been found to correlate with both PU and PEOU [56]. Some researchers reported that computer anxiety negatively impacts PEOU [30], [57] but does not affect PU [30]. In the context of RANX, studies by [28], [44], and [58] found that RANX negatively impacts PEOU. Based on this literature, the following hypotheses were formulated:

- H5: PSET's RANX negatively impacts their PEOU of EDRs for students with ASD.
- H6: PSET's RANX negatively impacts their PU of EDRs for students with ASD.

2.4 Job relevance (JOR)

Job relevance is "the degree to which an individual believes that the target system is applicable to his or her job" [59]. Individuals have varying perceptions of the outcomes they expect to achieve from technology depending on the nature of their jobs, and they are affected by external factors that impact their decisions regarding the technologies they require [60]. Thus, JOR affects employees' acceptance and use of innovative technological tools that have the potential to improve job performance and productivity. This study defines JOR as the degree to which a PSET believes that EDRs are applicable to their role in teaching students with ASD. Previous studies have shown that JOR influences the main constructs of the TAM model, namely PEOU and PU. For instance, [60] found that JOR impacts both PEOU and PU of information and communication technologies. Similarly, [40] found that JOR influences teachers' PEOU and PU regarding the use of e-learning. Despite the recognized importance of JOR in the acceptance of innovative technology in education, no studies have extended the TAM model to include JOR as an external variable influencing PU and PEOU in the context of EDR use by PSETs. Few studies have investigated its impact on robot technology; for example, [61] found that human resource professionals' PU of robotic assistance was influenced by JOR in the context of interviews. Additionally, [62] found that JOR influences employees' PU of human–robot collaboration, concluding that JOR is a key predictor of PU in the robot acceptance model. Based on this, two hypotheses were formulated:

- H7: PSET's JOR positively impacts their PEOU of EDRs for students with ASD.
- H8: PSET's JOR positively impacts their PU of EDRs for students with ASD.

2.5 Attitude and intention to integrate EDRs in the learning environment LMS

Attitude is an individual's readiness to respond favorably or unfavorably toward a psychological object, person, or subject [63–65]. It can lead to positive or negative feelings, shaped by prior interactions [65]. Therefore, a teacher's attitude toward EDRs reflects their readiness to respond favorably or unfavorably to integrating and using EDRs in their teaching practices. Attitude toward technology is a core construct in the TAM model, which influences the intention to use technology and is influenced by both PEOU and PU. These influences have been confirmed by several studies in various contexts [66], though few have investigated attitudes toward robots. For example, [67] found that users' attitudes toward service robots were influenced by both PEOU and PU. Similarly, [33] confirmed that PU and PEOU positively influenced users' attitudes toward robots used as teaching assistants.

Based on the theory of planned behavior (TPB), an individual's actions are influenced by three main constructs: attitude toward the behavior, subjective norm (which relates to social pressure to perform or not perform the behavior), and self-efficacy; this means that attitudes contribute to the development of behavioral intention [65]. Intention to use refers to "the degree of the cognitive state of the users' minds to use specific devices and technologies" [21]. Intention to use technology plays an important role in its actual use [68]. Researchers have investigated factors influencing the intention to use different technological tools using the extended TAM model in various contexts. For example, [40] found that PEOU, PU, and JOR are key determinants of teachers' intention to use e-learning. Additionally, [67] found that users' attitudes toward service robots impact their intention to use them. However, [69] indicated a lack of studies investigating behavioral intention toward AI among PSETs. A study by [33] also found that the intention to use robots as teaching assistants is influenced by users' attitudes toward them. Therefore, the following hypotheses were proposed:

- H9: PSET's PEOU of EDRs for students with ASD positively impacts their 'attitude toward integrating EDRs.
- H10: PSET's PU of EDRs for students with ASD positively impacts their 'attitude toward integrating EDRs.
- H11: PSET's candidate's attitude toward integrating EDRs positively impacts their intention to integrate EDRs for students with ASD's learning.

Based on the above recent studies and the literature on the TAM model, this study formulates a proposed extended TAM model and hypotheses as shown in Figure 1. The study aims to examine the influencing factors on the intention to integrate EDRs among preservice SETs in teaching students with ASD using SEM. The TAM model is expanded by including external factors—RSE, job relevance, robot anxiety, and social influence—to investigate their impact on the intention to integrate EDRs into ASD students' learning. The importance of this study lies in the fact that it is the first of its kind conducted in the context of Jordan and one of the few studies in this study area, helping to fill a gap in the field. Furthermore, the findings could assist decision-makers in developing policies to promote the acceptance and use of EDRs for students with ASD, ultimately enhancing the quality of their learning.

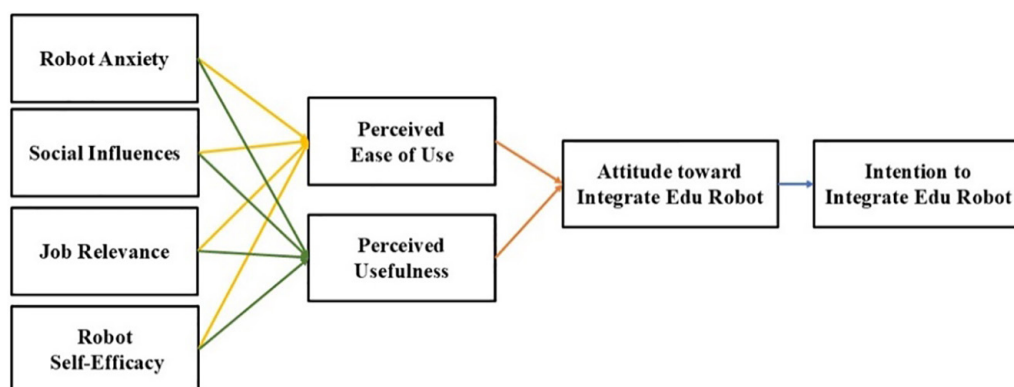


Fig. 1. The proposed extended TAM model of the study

3 RESEARCH METHODOLOGY

This study followed a quantitative research method using a random sampling approach and employed SEM techniques to investigate the relationships between study variables. The researcher extended the TAM model to explore the influence of external variables—RSE, RANX, social influence, and JOR—on the intention to integrate EDRs for students with ASD among PSETs. A web-based, self-administered questionnaire was used to collect data. The study was conducted at three randomly selected public universities in Jordan during the first term of the 2024–2025 academic year. Ethical approval and consent to conduct the study were obtained. The study was approved by the Institutional Review Board (IRB) at the University of Jordan (Approval No. 272/2024). Participants were informed about the study’s objectives, assured that their responses would remain confidential and anonymous, and provided consent to participate. They were also informed of their right to withdraw from the study at any time.

3.1 Participants, data collection

The study population consists of all second-, third-, and fourth-year undergraduate students enrolled in the Bachelor of Special Education program at public universities in Jordan and registered for the first semester of the 2024–2025 academic year. Three universities were selected using a simple random sampling technique. The researcher prepared a list of all public universities in Jordan offering a bachelor’s program in special education. Each university was assigned a sequential number, and random papers were drawn to select three universities in an unbiased manner, ensuring a representative and impartial sample. Data were collected during the second month of the first term of 2024–2025. All participants had the opportunity to be included in the study sample, as the web-based questionnaire link was distributed via WhatsApp and Facebook PSET groups, as well as through Teams and Moodle platforms. Data were collected over a period of three weeks. Participants were given clear instructions on how to complete the questionnaire. A total of 595 students (36 male and 559 female) participated in the study. They were drawn from three public universities: the UOJ, Hashemite University (HU), and Mutah University (MU). Table 1 displays the demographic profile of the study sample.

Table 1. Demographic profile of the respondents (N = 595)

No.	Variable	Value	P	F
1	Gender	Male	6.1%	36
		Female	93.9%	559
2	Academic level	Second	36.3%	216
		Third	26.7%	159
		Fourth	37.0%	220
3	GPA	Poor	6.2%	37
		Good	42.4%	252
		Very good	41.5%	247
		Excellent	9.9%	59
4	Level of technological skills	Basic	5.7%	34
		Intermediate	67.4%	401
		Advanced	25.4%	151
		Expert	1.5%	9
5	The university	UOJ	36.6%	218
		HU	33.6%	200
		MU	29.7%	177
		Total	100%	595

Note: F: frequency, P: percentage.

3.2 Data collection tools

The data for this study were collected using a web-based self-administered questionnaire consisting of two parts. The first part related to the demographic characteristics of the participants and included five items: gender, GPA, year of study, university affiliation, and technological skills. The second part comprised eight adapted scales designed to measure the study's latent variables: the RANX, which included four indicators assessing PSETs' levels of anxiety regarding the use of EDRs; the SI scale, with four indicators measuring the impact of peers, teachers, parents, and others on PSETs' intentions to integrate EDRs; the JOR, which included three indicators assessing how PSETs perceive the importance of EDRs in relation to their future instructional practices for students with ASD; the RSE, consisting of four indicators that measure PSETs' self-efficacy in integrating EDRs into their teaching of students with ASD; the PEOU scale (PEOU), with four indicators evaluating how easy PSETs believe it is to use EDRs in teaching students with ASD; the PU scale, composed of four indicators assessing how beneficial PSETs find the integration of EDRs in teaching students with ASD; the attitude toward integrating EDRs scale (ATIR), consisting of four indicators measuring PSETs' attitudes toward integrating EDRs; and the behavioral intention to integrate EDRs scale (BITIR), which included three indicators assessing PSETs' intentions to integrate EDRs into their teaching practices for students with ASD. Each scale was adopted from relevant theoretical literature and validated instruments. A 5-point Likert scale was used for all items: "1 indicated strongly disagree, 2 disagree, 3 neutral, 4 agree, and 5 strongly agree."

Researchers ensured the content validity of each scale through a panel of 12 educational experts from Jordanian universities specializing in counseling and mental health, special education, educational psychology, measurement and evaluation, clinical psychology, and educational technology. After these experts reviewed the tools, the researchers administered the study questionnaire to a pilot group consisting of 45 preservice SETs from the same population but not included in the main study sample. The collected data were used to compute statistical measures, including Cronbach’s alpha (α) and Pearson correlation coefficients (Pr) for each scale. The results of α and the item-total correlations for each scale are presented in Table 2. Pr were computed between individual items and their respective subscale totals, all yielding statistically significant results at $p < 0.05$ and falling within acceptable limits. Furthermore, α values for each subscale, shown in Table 2, supported the instrument’s reliability and construct validity.

Table 2. Reliability indices and item-total correlations

Scale (LV)	I	Statements	References	Range of ITC	α
PEOU	1	My interactions with EDRs are clear and easy to understand.	[25] [70]	0.778–0.863	0.849
	2	I find it simple to learn how to use EDRs for teaching students with ASD.			
	3	My students with ASD can easily use EDRs in their learning activities.			
	4	Using EDRs requires minimal mental effort for both special education teachers and students with ASD.			
PU	5	Utilizing EDRs boosts my academic productivity as a teacher for students with ASD.	[26]	0.836–0.854	0.804
	6	Incorporating EDRs is beneficial for supporting students with ASD.			
	7	Utilizing EDRs enhances my effectiveness as a teacher for students with ASD.			
SI	8	People who influence my behavior believe that I should integrate EDRs in education.	[25] [26]	0.802–0.864	0.860
	9	Individuals who matter to me believe that I should integrate EDRs in education.			
	10	My classmates believe that teachers should integrate EDRs into their teaching practices.			
	11	My special education instructors support the use of EDRs for teaching students with ASD.			
RSE	12	I do not feel comfortable integrating EDRs into the learning process for students with ASD.	[71] [27]	0.721–0.849	0.799
	13	I could easily use EDRs for students with ASD.			
	14	I possess the required competencies to effectively utilize EDRs in teaching students with ASD.			
	15	I feel capable of effectively using EDRs for students with ASD.			

(Continued)

Table 2. Reliability indices and item-total correlations (*Continued*)

Scale (LV)	I	Statements	References	Range of ITC	α
JOR	16	In my role as a PSET, the use of EDRs is important.	[72]	0.867–0.888	0.853
	17	In my role as a PSET, the use of EDRs is relevant to the educational process.			
	18	Integrating EDRs is relevant to the range of tasks I perform when supporting students with ASD.			
RANX	19	I feel unafraid when using EDRs.	[72]	0.473–0.912	0.832
	20	Engaging with EDRs tends to make me feel anxious.			
	21	Using EDRs creates a sense of discomfort for me.			
	22	I experience a sense of uneasiness when dealing with EDRs.			
BITIR	23	If the EDRs were permanently available, I would enthusiastically use them to enhance learning for students with ASD.	[28]	0.864–0.907	0.869
	24	If the EDRs were permanently available, I would consider using them to support learning for students with ASD.			
	25	I intend to incorporate the EDRs into my future teaching practices for students with ASD.			
ATIR	26	Incorporating EDRs to support students with ASD is a great idea.	[26]	0.868–0.889	0.901
	27	Integrating EDRs into my teaching is a wise decision for boosting student with ASD engagement.			
	28	I like the idea of using EDRs to assist in student ASD learning.			
	29	I have positive feelings about integrating EDRs into my teaching students with ASD practices.			

Note: α : Cronbach's alpha; LV: Latent Variable; I: Indicators; ITC: Item-Total Correlation.

3.3 Data analysis

Structural equation modeling serves as a suitable analytical approach for exploring variable interrelationships, including both direct and indirect influences on underlying latent constructs [73–75]. First, the model was constructed by defining the latent factors (i.e., robot anxiety, RSE, job relevance, and social influence) along with their corresponding observed indicators. Pearson's correlation was then conducted to explore relationships between variables, followed by SEM using the maximum likelihood method in AMOS to test the hypothesized model. Preliminary analysis included descriptive statistics (i.e., mean (M) and standard deviation (SD)) and Pearson correlation between variables. Assumptions of normality (i.e., skewness and kurtosis), linearity, and multicollinearity (i.e., Variance Inflation Factor (VIF)) were assessed. Fit indices, including the Chi-square (χ^2) test, Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA), were extracted to evaluate the model fit and

determine the relationships between constructs and their impact on the intention to integrate EDRs into teaching practices. Model fit indices were assessed to ensure the goodness-of-fit of the proposed model. The results from the SEM analysis identified key factors influencing PSETs’ intentions to integrate EDRs into teaching students with autism. All data were processed using AMOS software version 24.

4 FINDINGS

4.1 Initial analyses

Descriptive and inferential statistics were employed to explore central tendencies and intercorrelations among the underlying theoretical constructs and are presented in Table 3, showing significant correlations among the variables, with most being positive. However, RANX demonstrated negative correlations with PEOU, PU, attitude, and behavioral intention. To evaluate the normality of the dataset, skewness and kurtosis metrics were analyzed. The results demonstrated that the data followed an approximately normal distribution, with skewness ranging from -0.906 to 0.118 and kurtosis values between -0.929 and 0.747 [76].

Table 3. Summary measures and interrelationships among the study constructs

Variable	M	SD	PEOU	PU	SI	RSE	JOR	RANX	BITIR	ATIR
PEOU	3.91	0.79	1							
PU	4.11	0.68	.667**	1						
SI	3.96	0.71	.698**	.727**	1					
RSE	3.65	0.83	.652**	.518**	.716**	1				
JOR	4.02	0.79	.670**	.700**	.768**	.648**	1			
RANX	3.25	0.91	-.308**	-.157**	.376**	.544**	.252**	1		
BITIR	4.06	0.77	.620**	.702**	.714**	.542**	.752**	-.227**	1	
ATIR	4.11	0.76	.612**	.699**	.713**	.519**	.748**	-.153**	.826**	1

Notes: p < 0.01 for all correlations. **correlation is significant at the 0.01 level (2-tailed).

The assumption of linearity was assessed, and the results are displayed in Table 4, where all VIF values fell within an acceptable range of 1.262 to 3.977—well below the critical threshold of 10—indicating the absence of multicollinearity concerns [77].

Table 4. VIF results among latent variables

Variable	PEOU	PU	SI	RSE	JOR	RANX	BITIR	ATIR
PEOU		2.346	2.636	2.852	2.827	2.813	2.798	2.830
PU	2.681		2.477	2.339	2.480	2.505	2.502	2.501
SI	3.952	3.679		3.670	3.811	3.910	3.977	3.910
RSE	2.705	2.887	2.661		2.769	2.387	2.896	2.897
JOR	3.519	3.509	3.390	3.396		3.527	3.408	3.427
RANX	1.531	1.505	1.498	1.262	1.520		1.521	1.503
BITIR	3.842	3.761	3.829	3.845	3.689	3.820		2.799
ATIR	3.848	3.809	3.771	3.854	3.716	3.782	2.803	

4.2 Goodness of fit statistics

A critical ratio for differences indicated a significant difference at $p < 0.05$. The model's goodness-of-fit was evaluated using key indices: χ^2 was 3.362, the CFI was 0.931, and the RMSEA was 0.063. The model fit was deemed acceptable, as χ^2 was less than 5, CFI exceeded 0.90, and RMSEA fell within the acceptable range of 0.06–0.10 [78–79]. These results indicate that the model effectively represents the data and captures the relationships among the variables.

4.3 Test of the measurement pattern

As shown in Figure 1 and Table 5, RSE, SI, and JOR directly affected PEOU. Furthermore, SI, RANX, and JOR had a direct effect on PU. PU also directly influenced ATIR; however, PEOU had no significant effect on ATIR. Finally, ATIR had a direct impact on BITIR. The model accounted for 92% of the variance in BITIR, 83% in ATIR, 91% in PU, and 71% in perceived ease of use.

Table 5. Direct values between latent variables

Hypotheses	Path	Direct Effect	Result
H1	RSE → PEOU	0.312*	supported
H3	SI → PEOU	0.298*	supported
H5	RANX → PEOU	−0.032	unsupported
H7	JOR → PEOU	0.279*	supported
H2	RSE → PU	0.024	unsupported
H4	SI → PU	0.490*	supported
H6	RANX → PU	−0.151*	supported
H8	JOR → PU	0.481*	supported
H9	PEOU → ATIR	0.029	unsupported
H10	PU → ATIR	0.887*	supported
H11	ATIR → BITIR	0.958*	supported

Note: * $P < 0.05$, supported = the path is statically significant.

Table 5 shows that hypotheses H1, H3, H4, H6, H7, H8, H10, and H11 were accepted, suggesting positive impacts of RSE, SI, and JOR on PEOU, as well as positive effects of SI and JOR on PU. Additionally, PU had a positive influence on ATIR, and ATIR on BITIR. The results also reveal a negative impact of RANX on PU. Also, hypotheses H2, H5, and H9 were rejected, indicating no significant impact of RSE on PEOU, no effect of RSE on PU, and no influence of PEOU on ATIR. Figure 3 presents the measurement model with standardized path coefficients showing the relationships between the latent constructs and their observed indicators. The model illustrates how each construct—PEOU, SI, JOR, RSE, PU, ATIR, and BITIR—correlates with its respective observed variables. The path coefficients represent the strength of these relationships, with some paths indicating stronger associations than others. These findings support the proposed relationships and provide insights into how the constructs influence one another within the context of integrating robots into teaching students with autism spectrum disorder.

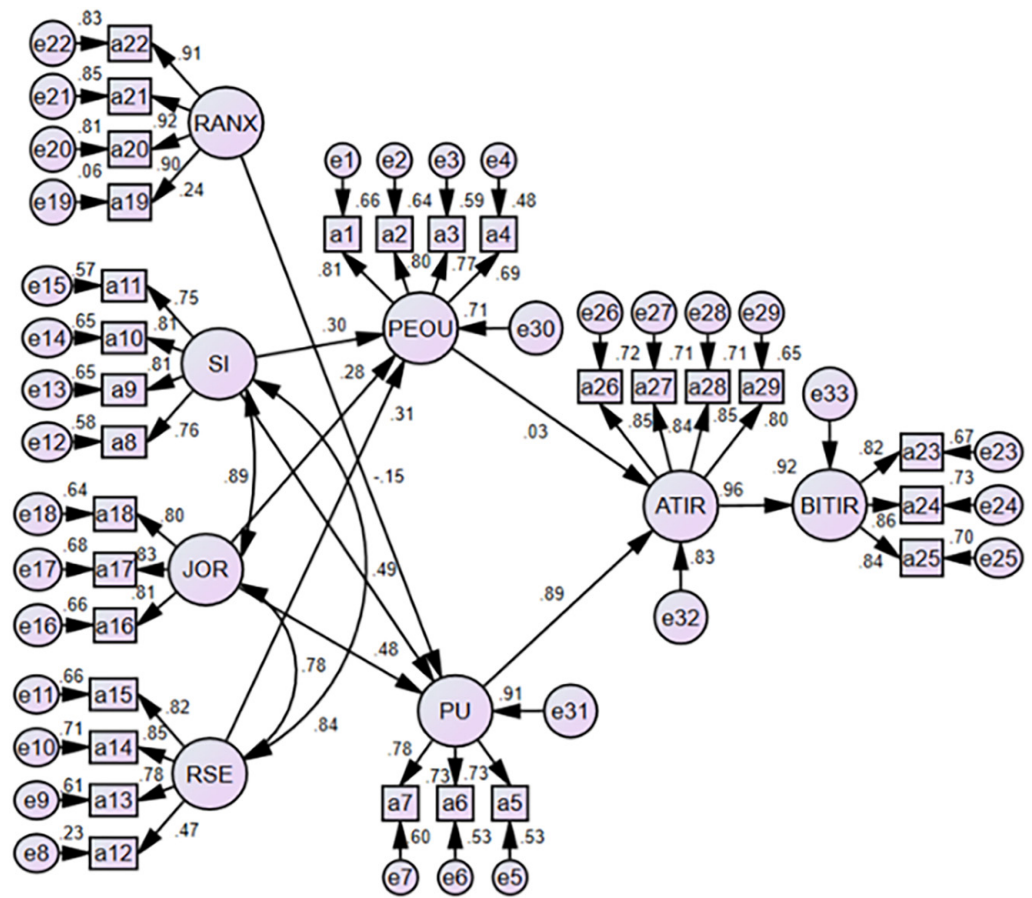


Fig. 2. Measurement model and relationships among constructs

5 DISCUSSION

This study highlights the important role of psychological, social, and professional factors impacting PSETs’ intention to integrate EDRs for students with ASD. The results indicate that PU is the most significant external factor affecting attitudes toward integrating robots for ASD students, whereas PEOU had no significant effect on these attitudes. Additionally, ATIR had a strong and significant impact ($\beta = 0.958$) on the behavioral intention to integrate robots for students with ASD. These findings emphasize the importance of developing positive attitudes to motivate PSETs to adopt and integrate EDRs in their teaching practices. This supports prior studies that revealed users’ attitudes toward service robots impact their intention to use them [67] and aligns with [33], which found that the intention to use robots as teaching assistants is influenced by attitudes toward them. Furthermore, these results are consistent with the TAM model, which suggests that users’ perceptions of a technology’s usefulness drive their attitudes and intention to use it [59]. The lack of a significant effect of PEOU on ATIR suggests that PSETs prioritize the practical benefits of EDRs for students with ASD over concerns about ease of use. Theoretically, this can be explained by SETs weighting performance expectancy (i.e., the expected impact on student outcomes) more heavily than effort expectancy, so PU dominates attitude formation. This aligns with [80], who found that performance expectancy outweighs effort expectancy in technology acceptance, particularly in contexts of effective integration in teaching and learning.

This is also supported by [81], who found that higher performance expectancy increases science teachers' intention to adopt humanoid robots. Practically, preservice teachers in inclusive education may focus more on the potential gains for students than on the complexity of the tools. Also, [36] found that the intention to use ERs for special needs students was predicted by perceptions of usefulness. This finding aligns with previous research, such as [15], which found that robot acceptance and usage decisions are influenced by the technology's effectiveness in supporting children with ASD. These insights suggest that future efforts should prioritize demonstrating the effectiveness and benefits of EDRs rather than focusing solely on ease of use.

Furthermore, the findings reveal that a set of external factors—(SI, JOR)—directly and positively impact both PEOU and PU among SETs. This indicates that encouragement from peers and mentors, such as teachers or school leaders, contributes to the perception that EDRs are easy to use, beneficial, and valuable in enhancing learning for students with ASD. These findings suggest that fostering a supportive institutional culture and encouraging collaboration among educators may be key to increasing robot integration in special education. Additionally, they indicate that SETs are more likely to perceive EDRs as beneficial and easy to use when they see them as directly relevant to their instructional responsibilities and teaching practices with ASD students. These findings align with previous studies that found SI significantly impacts PU in the context of e-learning [48] and with [44], which found that subjective norms positively influence PU in the use of robots in production. Similarly, [50] emphasized the direct effect of normative beliefs on social robot acceptance, and [51] supported their positive effect on PU. The findings are also consistent with studies showing the influence of SI on PU and PEOU in other contexts, such as the adoption of energy and smart technology solutions [47], [52]. However, these results contradict [48], which found no teacher influence on PEOU in e-learning, and [28], which found that subjective norms did not impact PU in a market context. Additionally, this study supports prior research demonstrating that JOR impacts PEOU in contexts like the use of ICTs and e-learning [60]. The results from [40] underscore the importance of designing professional development programs that explicitly demonstrate how robots can be seamlessly integrated into teachers' daily instructional practices.

Furthermore, the findings reveal that RSE significantly and directly impacts PEOU among PSETs but not PU. This indicates that teachers with higher RSE—who feel more confident in their ability to use robots—are more likely to perceive EDRs as easier to use and find it easier to incorporate them into their teaching practices with students with ASD. This aligns with previous research confirming a relationship between technology self-efficacy and the use of technological tools [41–42]. It also supports the study by [44], which found that self-efficacy correlates with PEOU in the context of human-robot cooperation, and is further supported by [28], which confirmed the impact of RSE on the PEOU of social robots among early adopters. Additionally, it aligns with [41], which found that self-efficacy impacts teachers' positive attitudes toward employing technologies in their instructional programs. Similarly, [42] found that self-efficacy is positively related to university students' deep learning approaches when using online learning technologies. These results are also supported by several previous studies showing a link between technology self-efficacy and the use of technological tools [41–42]. However, the findings contradict those of [69], which reported no significant impact of teacher AI self-efficacy on perceptions of using AI. These contradictory findings highlight the need for further studies to examine the impact of RSE in the context of special education.

However, the study also revealed that RANX has a negative direct impact on PU. The results suggest that PSETs who experience higher levels of anxiety regarding

EDRs are less likely to view them as beneficial tools for teaching students with ASD. This aligns with research showing that technology-related anxiety can be a barrier to adoption [13] and negatively correlates with PU [56]. These findings imply that RANX among PSETs could be reduced through training and that encouragement from institutions and stakeholders may improve teachers' perceptions of the usefulness of EDRs. However, the study found no significant direct effect of RANX on PEOU, suggesting that RANX does not necessarily hinder the perceived ease of using robots among SETs. With adequate training and exposure, they may overcome anxiety. This finding contradicts prior studies [28], [44], and [58], which may be attributed to differences in context and highlight the need to replicate this study to confirm the results.

From a practical perspective, these findings offer important implications for educational policymakers and curriculum designers. Encouraging the adoption of EDRs in special education requires strategies that foster a positive social environment, clearly demonstrate the JOR of EDRs for students with ASD, and implement targeted interventions to reduce associated anxiety. Therefore, special education teacher preparation programs should emphasize the practical benefits of EDRs through real-world success stories, field experiences, and peer collaboration to reinforce positive attitudes and increase adoption rates.

6 CONCLUSIONS

This study contributes to bridging the gap in research on the integration of educational technology in special education. Specifically, to the best of our knowledge, it is the first study conducted in Jordan—and one of the few globally—that investigates the factors impacting the intention to integrate EDRs for students with autism by examining the psychological, social, and professional factors affecting PSETs' intentions to adopt EDRs for students with ASD. The findings revealed that PU is the primary driver of positive attitudes toward robot integration. Attitude, in turn, emerged as the strongest predictor of behavioral intention, highlighting the importance of fostering favorable perceptions to ensure successful implementation. SI and JOR were identified as critical external factors shaping both PEOU and usefulness. Moreover, RSE enhanced perceptions of ease of use, while RANX negatively affected perceived usefulness, suggesting that emotional barriers can hinder acceptance even when usability is not a concern.

These findings encourage decision-makers to develop policies and implement technical training that promotes a supportive culture, demonstrates the instructional value of EDRs, and addresses emotional readiness. By emphasizing real-world applications and collaborative experiences, such programs can better prepare future educators to use robotic technologies in inclusive classrooms and enhance the learning experience for students with ASD. However, it is important to acknowledge some limitations and their implications. The sample size included a limited number of male students, which may limit the applicability of the findings to male preservice teachers and obscure possible gender-related differences, thereby constraining generalizability. Future research should include broader and more diverse samples from various contexts to validate and extend these results. Additionally, the cross-sectional nature of the study prevents conclusions about causality from being drawn; the reported relationships should therefore be interpreted as correlational. Future studies are recommended to use longitudinal or experimental designs to track actual usage behavior over time and confirm causal relationships.

7 REFERENCES

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