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Teacher adoption of artificial intelligence in autism education: A contextual UTAUT study in Saudi Arabia

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Abstract

Artificial intelligence is receiving growing attention in autism education, but less is known about the factors associated with teachers' intention to use it and their self-reported use in Saudi Arabia. This study examined these relationships using the Unified Theory of Acceptance and Use of Technology framework. A quantitative cross-sectional online survey was completed by 400 special-education teachers in Saudi Arabia. The 25-item questionnaire measured performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and self-reported use. The measurement model and the hypothesized relationships among these constructs were examined using confirmatory factor analysis and structural equation modeling. The findings supported the proposed measurement structure and all five hypothesized relationships. Performance expectancy showed the strongest association with behavioral intention, while behavioral intention and facilitating conditions were positively associated with self-reported use. Overall, the findings indicate that teachers' adoption of artificial intelligence was associated with both their perceptions of the technology and the conditions supporting its use. Within this sample, teachers' intentions and self-reported use of artificial intelligence were associated with both individual perceptions and enabling school conditions. The study extends technology-adoption evidence to special-education teachers working in autism education in Saudi Arabia and highlights the importance of considering both intention and practical implementation conditions. The findings do not establish causal effects or observed classroom use.

Keywords: Artificial intelligence; Autism education; Special education; Teachers; UTAUT

1. Introduction

Digital transformation has changed everyday teaching, including lesson planning, delivery, and assessment (Villarin et al., 2025). Artificial intelligence (AI) has become part of this change through developments in data analytics, natural language processing, and machine learning (Chen et al., 2020; Holmes et al., 2019). In schools, AI may support adaptive assessment, learning analytics, recommendation systems, affective computing, and educational robotics (Pandya et al., 2024). However, availability alone does not mean that a tool can be used well. Its value depends on whether it fits curriculum goals, classroom routines, teacher preparation, and the resources available in schools (Chen et al., 2020; Iannone & Giansanti, 2024).

In special education, AI may support more responsive and inclusive instruction for students with autism spectrum disorder (ASD) (Habibi et al., 2025). Examples include socially assistive robots, guided practice systems, and tools that support attention, engagement, communication, or affect recognition (Dautenhahn, 2007; Rudovic et al., 2018). Some studies suggest that such tools may support participation and instructional decisions when teachers can use the information meaningfully in classroom practice (Kotsi et al., 2025; Lampos et al., 2021). However, the evidence is still limited by small samples, device-specific studies, and short-term designs (Kotsi et al., 2025; Li et al., 2024).

Much of the existing literature focuses on system design or learner outcomes in controlled settings. Less is known about how teachers judge whether AI tools fit lesson goals, learner profiles, and everyday classroom limitations (Ke et al., 2022). This matters because teachers' decisions and the conditions within schools may shape whether a tool is used in routine practice (Hazzan-Bishara et al., 2025; Li et al., 2024).

Recent studies in Saudi Arabia and the United Arab Emirates have begun to examine teacher readiness and AI adoption in school settings (Alhaif et al., 2025; Fteiha et al., 2025). Recent Saudi university-student studies also report that AI adoption may be associated with readiness, interactivity, ethical awareness, perceived value, ease of use, and social influence (Alshammari et al., 2025; Alshammari et al., 2026). Taken together, this regional evidence suggests that both individual perceptions and enabling conditions may be relevant to AI adoption. However, the available studies differ substantially in their populations and outcomes, with much of the Saudi evidence focusing on university students and broader educational contexts rather than teachers working specifically in autism education. As a result, it remains unclear whether these relationships operate similarly among Saudi special-education teachers or how behavioral intention relates to their recent self-reported use.

Recent empirical work across different educational contexts provides broadly consistent support for the relevance of perceived value, ease of use, and social or institutional influences in teachers' AI adoption, although the relative importance of these factors varies across settings. Zhao et al. (2025) examined AI adoption among Chinese middle-school teachers, while Velli and Zafiropoulos (2024) studied Greek teachers' acceptance of educational AI tools. Using a framework based on the Unified Theory of Acceptance and Use of Technology (UTAUT), Trung et al. (2025) similarly found that performance expectancy, effort expectancy, and social influence were associated with Vietnamese mathematics teachers' behavioral intention to use ChatGPT. López-Costa et al. (2025) examined secondary-school teachers in Catalonia, and Zraydi et al. (2026) applied UTAUT to teachers working with students with learning disabilities in the United Arab Emirates. Related research has also examined AI acceptance among university faculty, although this represents a different professional and educational context from school-based special education (Bilgin & Güngören, 2025). Across these studies, AI adoption has primarily been examined among mainstream schoolteachers, higher-education educators, or teachers working with learning disabilities, and the outcomes have often centered on acceptance or behavioral intention. Evidence remains limited regarding special-education teachers working specifically with students with autism and regarding models that distinguish future behavioral intention from recent self-reported use.

In this study, AI tools refer to educational applications that use artificial intelligence techniques, such as machine learning, natural language processing, adaptive algorithms, or intelligent automation. These applications may support instruction, assessment, feedback, or personalized learning (Chen et al., 2020). In autism education, they may also be used to personalize learning, monitor progress, and adapt teaching materials to students' needs (Hussein et al., 2025). The term is used here in a classroom and instructional sense, rather than as a general reference to AI in unrelated fields.

Although AI has received increasing attention in Saudi educational and special-education research, evidence remains limited regarding its adoption specifically among teachers working with students with autism (Alhaif et al., 2025; Alsudairy & Eltantawy, 2024). Existing studies provide useful evidence concerning perceptions, readiness, barriers, or adoption intention, but they do not establish how the core UTAUT relationships operate in this specialized Saudi teaching context. In particular, little is known about whether performance expectancy, effort expectancy, and social influence are associated with teachers' behavioral intention and whether behavioral intention and facilitating conditions are separately associated with recent self-reported AI use. A platform may be available without being used consistently in teaching. For this reason, it is important to examine the factors associated with teachers' behavioral intention and self-reported use of AI in autism education.

To address this gap, this study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine teachers' adoption of AI tools in autism education in Saudi Arabia (Venkatesh et al., 2003). UTAUT is useful because it considers not only whether a teacher sees a tool as useful or easy to use, but also the social and organizational conditions that may shape use in schools (Ajzen, 1991; Scherer et al., 2019; Venkatesh et al., 2003).

UTAUT was developed by integrating elements from several earlier technology-acceptance models, including the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) (Venkatesh et al., 2003). TAM focuses on perceived usefulness and perceived ease of use, which are conceptually related to performance expectancy and effort expectancy in UTAUT (Scherer et al., 2019; Venkatesh et al., 2003). TPB explains behavioral intention through attitudes, subjective norms, and perceived behavioral control. Subjective norm is closely related to social influence, while perceived behavioral control overlaps partly with the practical-control and resource considerations represented by facilitating conditions (Ajzen, 1991; Venkatesh et al., 2003). TAM and TPB are therefore important foundations, but UTAUT is more suitable here because it combines expectancy beliefs with professional influence and institutional support and distinguishes behavioral intention from self-reported use. This is relevant in autism education, where teachers must fit AI tools to learner needs, instructional plans, classroom routines, training, and available school support (Kittinger & Law, 2024).

The study examines whether performance expectancy, effort expectancy, and social influence are positively associated with behavioral intention. It also examines whether behavioral intention and facilitating conditions are positively associated with teachers' self-reported use. The measurement model and the proposed relationships were assessed using confirmatory factor analysis (CFA) and structural equation modeling (SEM).

The study makes a specific but bounded contribution to the literature on teacher adoption of AI. First, it extends existing UTAUT-based evidence to special-education teachers working specifically in autism education in Saudi Arabia, a professional context that has received limited attention in previous teacher-adoption research. Prior studies have examined AI acceptance or intention among mainstream teachers in different educational systems and among teachers working with students with learning disabilities, while recent Saudi UTAUT research has focused primarily on university students (Alshammari et al., 2026; Trung et al., 2025; Zraydi et al., 2026). Second, the study distinguishes future-oriented behavioral intention from recent self-reported use, allowing the established UTAUT relationships associated with intention and self-reported use to be examined separately within the same model. Third, it provides measurement and structural evidence for these relationships in a specialized educational setting where technology use must be aligned with individualized learner needs and classroom practice. The contribution is therefore contextual and empirical rather than a proposal for a new or extended UTAUT model, and the cross-sectional design does not establish causal or temporal relationships.

1.1 Hypotheses

H1: Performance expectancy is positively associated with teachers' behavioral intention to use AI technologies in autism education.

H1 examines whether teachers' behavioral intention is related to the instructional value they expect from AI. UTAUT treats performance expectancy as an important factor in technology acceptance, and teacher-adoption research has often identified perceived usefulness as relevant to intention (Kittinger & Law, 2024; Venkatesh et al., 2003; Xue et al., 2025). In this study, the hypothesis concerns teachers' expectations about teaching tasks. It does not assume that AI improves learner outcomes.

H2: Effort expectancy is positively associated with teachers' behavioral intention to use AI technologies in autism education.

H2 examines whether behavioral intention is related to the perceived effort required to use AI. A tool may be seen as useful but still be difficult to learn, set up, or fit into routine teaching. Previous studies suggest that ease of use remains relevant when teachers consider technologies that must work within everyday classroom practice (Acquah et al., 2024; Kahnbach et al., 2024; Venkatesh et al., 2003).

H3: Social influence is positively associated with teachers' behavioral intention to use AI technologies in autism education.

H3 examines whether behavioral intention is related to social influence. Teachers make decisions within professional settings where leadership messages, colleagues, and wider norms may shape how appropriate AI use appears. UTAUT and teacher-adoption research suggest that these social conditions can be relevant when educators consider new technologies (Acquah et al., 2024; Kittinger & Law, 2024; Venkatesh et al., 2003).

Recent Saudi UTAUT-based evidence reported positive associations of performance expectancy, effort expectancy, and social influence with university students' behavioral intention to use AI (Alshammari et al., 2026). That study informs the present hypotheses, but its student population and outcome do not provide direct evidence about special-education teachers or autism-related classroom practice.

H4: Facilitating conditions are positively associated with teachers' self-reported use of AI technologies in autism education.

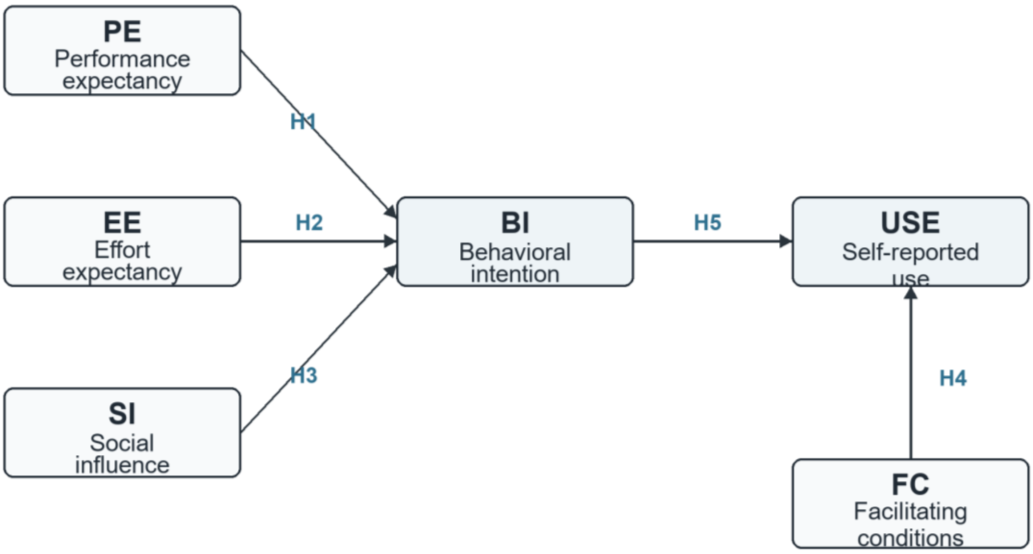
H4 focuses on whether facilitating conditions are associated with teachers' self-reported use of AI. Intention may be present even when access to devices, software, training, or technical support is limited. UTAUT therefore treats these practical conditions as relevant to technology use (Kittinger & Law, 2024; Venkatesh et al., 2003). Findings concerning facilitating conditions vary across AI-adoption contexts and outcomes. For example, facilitating conditions were not significantly associated with green-AI behavior among Jordanian university students (Alkhwaldi et al., 2026).

H5: Behavioral intention is positively associated with teachers' self-reported use of AI technologies in autism education.

H5 examines the relationship between behavioral intention and self-reported use. UTAUT proposes that intention is closely related to technology use, although use may also depend on the setting and available support (Kittinger & Law, 2024; Venkatesh et al., 2003). The hypothesis is therefore limited to the association between teachers' stated intention and their self-reported use within this study.

Figure 1 presents the proposed UTAUT structural model and the hypothesized relationships examined in this study.

Figure 1
Proposed UTAUT Structural Model



Note. H1–H5 represent the hypothesized paths. Covariances among PE, EE, SI, and FC were estimated but are omitted for clarity.

2. Methodology

2.1. Research Design

This study used a quantitative, descriptive-analytical, cross-sectional survey design guided by

UTAUT. It focused on special-education teachers who teach students with autism spectrum disorder in Saudi Arabia. UTAUT provided a framework for examining whether performance expectancy, effort expectancy, social influence, and facilitating conditions were associated with teachers' behavioral intention and self-reported use of AI tools (Venkatesh et al., 2003).

The descriptive component summarized teachers' perceptions and self-reported AI use in the Saudi educational context. The analytical component examined the relationships specified in the UTAUT model. These relationships involved performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and self-reported use.

A cross-sectional design was suitable because the study examined associations among teachers' perceptions, behavioral intention, and self-reported use at one period of data collection. However, this design does not establish causal direction or show how AI adoption may develop over time. The findings were therefore interpreted as associations within the study sample rather than causal effects (Wang & Cheng, 2020).

2.2. Participants and Sampling

The target population included special-education teachers who teach students with autism spectrum disorder in Saudi Arabia. The study used a non-probability purposive convenience and voluntary-response sampling approach because it targeted a specific group of teachers. Recruitment relied on institutional school channels and professional educational networks rather than random selection. The coordinators' role was limited to circulating the invitation, and they were not informed about which teachers chose to participate.

Because the sample was not randomly selected, it may not represent all special-education teachers working in autism education in Saudi Arabia. Teachers who were more active in professional networks, more comfortable with online questionnaires, or more interested in AI-related issues may have been more likely to participate. Eligible participants were required to be currently teaching students with ASD in Saudi Arabia and willing to participate voluntarily. Eligibility was assessed through the institution-based recruitment route and self-reported screening information. Records did not enter the final analysis when the available information indicated that the respondent was outside the target setting, did not meet the teaching criteria, or provided an incomplete, inconsistent, duplicate, or otherwise unusable response. Because participation was anonymous, eligibility was not independently verified against employment records.

Participants were instructed to complete the questionnaire only once. To protect anonymity, the survey did not collect names, email addresses, telephone numbers, employee identification numbers, or IP addresses. Identity-based or IP-based restrictions were therefore not applied. Before the analysis file was finalized, records were screened for incomplete responses, inconsistencies, data-entry errors, and potential duplicate submissions. Potential duplicates were identified by comparing the available demographic information and complete item-response patterns and were manually reviewed during data cleaning. Records judged duplicate, erroneous, or otherwise unusable were not retained. The final analysis-ready data set contained 400 complete and valid records.

To assess the adequacy of the final sample, a conventional regression-based power analysis was conducted for the largest structural predictor set. Using G*Power 3.1 and the F-test procedure for fixed-model multiple regression (R^2 deviation from zero), with three predictors, $\alpha = .05$, target power = .80, and a medium effect size of $f^2 = .15$, the required sample was 77 (Cohen, 1988; Faul et al., 2009). The final analytical sample of 400 exceeded this benchmark. This calculation provides a sample-adequacy check for the structural paths; it does not substitute for the CFA and SEM fit assessment.

The project records do not contain the number of teachers who received the invitation, accessed the survey, submitted a questionnaire, or were excluded at individual screening stages. Participant flow is therefore reported narratively rather than as a numerical flow diagram, and stage-specific exclusion counts cannot be provided. All 400 retained records had complete responses to the 25

UTAUT items and were included in the CFA and SEM. A formal response rate and a direct assessment of non-response bias could not be calculated. Table 1 presents the demographic profile of the respondents.

Table 1
Demographic Profile of Respondents (N = 400)

Variable	*n*	%
Gender		
Male	210	52.5
Female	190	47.5
Age Group		
Under 30	87	21.8
30-39	63	15.8
40-49	153	38.3
50 years and above	97	24.3
Highest academic degree		
Diploma	30	7.5
Bachelor	302	75.5
Master	32	8.0
PhD	36	9.0
Teaching experience		
Under 5 years	120	30.0
5-10 years	62	15.5
11-15 years	61	15.3
16 years or more	157	39.3

The sample included 210 male teachers (52.5%) and 190 female teachers (47.5%). The largest age group was 40-49 years (n = 153, 38.3%), followed by 50 years and above (n = 97, 24.3%). Most respondents held a bachelor's degree (n = 302, 75.5%), and 157 respondents (39.3%) reported 16 years or more of teaching experience.

2.3. Data Collection and Measures

Data were collected at one point in time through a secure Google Forms questionnaire. The data-collection period lasted two months, from 10 January 2026 to 10 March 2026. The invitation was distributed electronically through institutional email lists and closed internal WhatsApp groups used for routine school communication. Designated coordinators within participating schools and education programs circulated the survey link to eligible special-education teachers across different regions of Saudi Arabia. The link was not posted on public websites, unrestricted social-media groups, or open WhatsApp groups, and coordinators were not informed about individual participation.

The survey included two sections. Section A collected demographic information, including gender, age group, educational qualification, and teaching experience. Section B measured the UTAUT variables. Performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention used a 5-point agreement scale from 1 = strongly disagree to 5 = strongly agree. Self-reported use used a separate 5-point frequency scale for the previous four weeks, from 1 = never to 5 = several times per week.

Respondents were asked to understand AI tools as AI-enabled educational applications used in autism education. These applications could support teaching activities, personalized instruction, student progress monitoring or assessment, and the creation or adaptation of instructional materials. This approach is consistent with special-education research that describes AI as an instructional and assistive resource for learning, assessment, and adaptation (Hussein et al., 2025). The questionnaire therefore focused on practical teaching functions rather than one named software product or device.

Participants completed the Arabic version of the questionnaire, while the Appendix 1 presents the corresponding English wording for reporting purposes. The Arabic administration and English presentation were aligned to preserve the intended meanings of the UTAUT constructs and the contextualized teaching tasks. Because a formal translation-validation procedure was not conducted, the language versions are not presented as independently validated translations.

The questionnaire comprised 25 items across six constructs. Performance expectancy and effort expectancy each included five items. Social influence and facilitating conditions included four items, while behavioral intention included four items and self-reported use included three items. The item pool was developed for the present study and was not treated as a previously validated fixed 25-item scale. Performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention were grounded in the corresponding UTAUT constructs (Venkatesh et al., 2003).

Several items closely adapted established UTAUT wording concerning ease of learning, clarity, skill development, leadership or supervisor support, resources, technical assistance, and future intention to use technology. Other items were UTAUT-informed and contextually specified for AI-supported teaching in autism education, including personalized instruction, progress monitoring, instructional adaptation, school access, training, and professional acceptance. This construct-based approach was used to preserve the intended meaning of the UTAUT dimensions while adapting the wording to autism-education teaching tasks. Comparable teacher-context UTAUT measures provide precedent for adapting acceptance items to teaching tasks and school conditions (Kahnbach et al., 2024; Zhou et al., 2022), while the contextual specifications were supported by special-education and autism literature (Hussein et al., 2025; Kotsi et al., 2025; Rakap, 2024).

USE1–USE3 were developed for the present study as task-specific self-reported frequency indicators during the previous four weeks. They focused on AI-supported instructional preparation, adaptation to individualized learner needs, and communication-related materials. The items were designed to distinguish recent self-reported use from future behavioral intention and were not based on objective system logs or observational records (Pynoo et al., 2011).

Because the study used single-source self-reported questionnaire data, common method bias was considered as a possible concern. Participation was voluntary and anonymous, and the questionnaire used standardized wording and response scales. These features may reduce evaluation pressure and socially desirable responding. However, shared method variance cannot be ruled out because the core constructs were measured from the same respondents at one point in time (Podsakoff et al., 2003).

2.4. Data Analysis Procedures

Data screening and descriptive analyses were conducted using IBM SPSS Statistics, version 27. Confirmatory factor analysis and structural equation modeling were conducted using jamovi, version 28.2, with the SEMLj module.

Internal consistency was assessed using Cronbach's alpha, McDonald's omega, and composite reliability (CR). Omega was reported alongside alpha because it provides an additional model-based estimate of reliability when the assumptions underlying alpha may not fully hold (Dunn et al., 2014). CR was calculated from the fully standardized CFA loadings and the corresponding indicator error variances; values of .70 or higher were treated as acceptable (Fornell & Larcker, 1981). Convergent validity was assessed using standardized factor loadings and average variance extracted (AVE). Average variance extracted indicates the amount of variance captured by a construct relative to measurement error (Fornell & Larcker, 1981). Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT). HTMT was used to examine whether the six constructs were empirically distinct from one another (Henseler et al., 2015).

Confirmatory factor analysis was used to test the six-factor measurement model. Each item was specified to load on its intended construct: performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, or self-reported use. The six latent factors were allowed to correlate because the UTAUT constructs are theoretically related.

The questionnaire items were treated as ordinal indicators. The CFA was therefore estimated using diagonally weighted least squares (DWLS) with robust/scaled standard errors and fit statistics. This approach is appropriate for ordinal Likert-scale indicators because it does not require the items to be treated as fully continuous variables (Li, 2016).

Model fit was assessed using robust/scaled χ^2, comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA) with its 95% confidence interval, and standardized root mean square residual (SRMR). The fit indices were interpreted together because no single index provides a complete evaluation of model fit (Hu & Bentler, 1999). Standardized factor loadings were examined to assess the relationships between the observed items and their intended constructs.

Structural equation modeling was then used to test the hypothesized relationships. Performance expectancy, effort expectancy, and social influence were specified as factors associated with behavioral intention. Behavioral intention and facilitating conditions were specified as factors associated with self-reported use. The exogenous UTAUT constructs were allowed to correlate.

Indirect associations of performance expectancy, effort expectancy, and social influence with self-reported use through behavioral intention were also estimated. Robust/scaled fit statistics, standardized path coefficients, standard errors, 95% confidence intervals, z-values and p-values were reported. The proportion of explained variance was reported for behavioral intention and self-reported use. Statistical significance was set at $p < .05$. Because the data were cross-sectional and self-reported, the structural results were interpreted as associations rather than causal effects.

2.5. Ethical Considerations

This study was conducted in accordance with the Declaration of Helsinki and received ethical approval from the Institutional Review Board at Najran University. Participation was voluntary, and respondents were informed about the purpose of the study before completing the questionnaire.

Informed consent was obtained from all participants before data collection. Confidentiality and anonymity were maintained throughout the study. No personal identifying information was collected, and the data were used only for research purposes.

3. Results

3.1. Measurement Model Assessment

Table 2 presents the robust/scaled fit indices for the six-factor CFA measurement model.

Table 2
Robust/Scaled Fit Indices for the Six-Factor CFA Measurement Model

Fit statistic	*Result*	*Interpretation*
Robust/scaled χ^2	267	
df	260	
p	.368	Nonsignificant
Robust CFI	.995	Excellent
Robust TLI	.994	Excellent
Robust RMSEA	.018	Excellent
RMSEA 95% CI	.000–.035	Excellent
Robust SRMR	.031	Excellent

Note. Indicators were treated as ordinal and estimated using DWLS with robust/scaled fit statistics. Classical RMSEA is not used as the primary fit statistic.

The measurement model showed excellent overall fit. The scaled χ^2 test was nonsignificant, and the robust CFI, TLI, RMSEA, and SRMR values were all within recommended ranges.

Table 3 shows that reliability and convergent validity were satisfactory for all six constructs. All standardized factor loadings were acceptable and statistically significant ($p < .001$). The ranges were .753–.824 for PE, .687–.867 for EE, .734–.844 for SI, .737–.860 for FC, .787–.863 for BI, and .795–.831 for USE. EE4 had the lowest loading (.687), but it remained above the conventional minimum.

Internal consistency was assessed using Cronbach's alpha, McDonald's omega, and Composite Reliability. Composite Reliability values ranged from .854 to .898 and were above the recommended .70 threshold for all constructs, providing additional evidence of internal consistency.

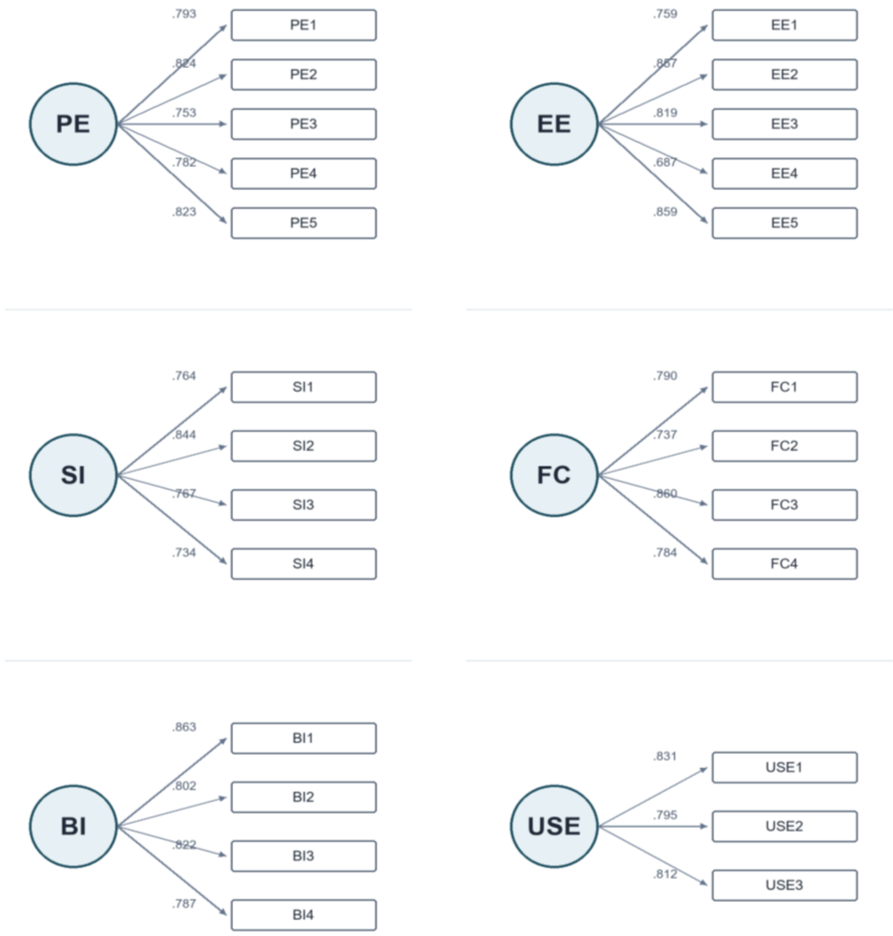
Table 3
Standardized Factor Loadings, Internal Consistency, and Convergent Validity

Construct	*Items*	*Loading range*	α	ω	*CR*	*AVE*
Performance Expectancy (PE)	5	.753–.824	.847	.859	.896	.633
Effort Expectancy (EE)	5	.687–.867	.846	.855	.898	.638
Social Influence (SI)	4	.734–.844	.820	.827	.860	.606
Facilitating Conditions (FC)	4	.737–.860	.796	.796	.872	.630
Behavioral Intention (BI)	4	.787–.863	.837	.841	.891	.671
Self-Reported Use (USE)	3	.795–.831	.803	.808	.854	.661

Note. All freely estimated standardized loadings were statistically significant at $p < .001$. α = Cronbach's alpha; ω = McDonald's omega; CR = composite reliability; AVE = average variance extracted.

Figure 2 displays the standardized six-factor CFA measurement model. The figure shows the standardized item loadings and omits numerical covariance values to keep the labels readable; latent-factor covariances were nevertheless estimated in the CFA. The displayed loadings correspond with Table 3.

Figure 2
Standardized Six-Factor CFA Measurement Model



Note. Standardized factor loadings are displayed. Latent-factor covariances were estimated but their numerical values are omitted for readability.

3.2. Discriminant Validity

Table 4 presents the HTMT values used to assess discriminant validity among the six constructs.

Table 4
Heterotrait–Monotrait Ratio of Correlations (HTMT)

	PE	*EE*	*SI*	*FC*	*BI*	*USE*
PE	1.000	.447	.474	.311	.611	.531
EE	.447	1.000	.429	.252	.469	.442
SI	.474	.429	1.000	.338	.522	.385
FC	.311	.252	.338	1.000	.436	.521
BI	.611	.469	.522	.436	1.000	.647
USE	.531	.442	.385	.521	.647	1.000

Note. PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; BI = behavioral intention; USE = self-reported use.

All HTMT values were below the recommended threshold of .85. The highest value was .647 for the BI–USE association, supporting discriminant validity among the six constructs.

3.3. Descriptive Analysis

Table 5 presents the construct descriptive statistics and Pearson correlations.

Table 5
Construct Descriptive Statistics and Pearson Correlations (N = 400)

Construct	*M*	*SD*	*PE*	*EE*	*SI*	*FC*	*BI*	*USE*
PE	3.76	0.92	1.000	.447	.474	.311	.611	.531
EE	3.71	0.82	.447	1.000	.429	.252	.469	.442
SI	3.14	1.08	.474	.429	1.000	.338	.522	.385
FC	1.92	0.95	.311	.252	.338	1.000	.436	.521
BI	4.01	1.01	.611	.469	.522	.436	1.000	.647
USE	3.57	1.08	.531	.442	.385	.521	.647	1.000

Note. All correlations were significant at $p < .001$. PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; BI = Behavioral Intention; USE = Self-Reported Use.

Behavioral intention to use AI tools was rated relatively highly (*M* = 4.01, *SD* = 1.01). The mean for self-reported use was 3.57 (*SD* = 1.08), which lay between two or three times and weekly during the previous four weeks. Performance expectancy (*M* = 3.76, *SD* = 0.92) and effort expectancy (*M* = 3.71, *SD* = 0.82) were also rated positively. Social influence was moderate (*M* = 3.14, *SD* = 1.08), while facilitating conditions had the lowest mean (*M* = 1.92, *SD* = 0.95).

3.4. Structural Model and Hypothesis Testing

Table 6 presents the robust/scaled fit indices for the ordinal DWLS structural equation model.

Table 6
Robust/Scaled Fit Indices for the Ordinal DWLS Structural Equation Model

Fit statistic	*Result*	*Interpretation*
Estimator	DWLS	Ordinal indicators
Observations	400	
Convergence	Yes (46 iterations)	
Scaled χ^2	331	
df	264	
p	.003	
Robust CFI	.988	Good
Robust TLI	.986	Good
Robust RMSEA	.026	Good
RMSEA 95% CI	.000–.041	
Robust SRMR	.038	Good

Note. The scaled χ^2 test is reported with robust fit indices because the indicators were modeled as ordinal.

The structural model converged after 46 iterations, and the robust fit indices indicated good overall fit. Although the scaled χ^2 test was statistically significant (p = .003), the CFI, TLI, RMSEA, and SRMR values supported satisfactory model fit.

All five hypothesized structural paths were positive and statistically significant (Table 7).

Table 7

Structural Direct and Indirect Associations in the SEM

Path	B	*β*	*z*	*95% CI for B*	*p*	*Decision*
H1: PE → BI	0.485	.448	7.46	0.358–0.613	< .001	Supported
H2: EE → BI	0.231	.206	3.60	0.105–0.357	< .001	Supported
H3: SI → BI	0.265	.236	4.02	0.136–0.395	< .001	Supported
H4: FC → USE	0.375	.355	6.41	0.260–0.489	< .001	Supported
H5: BI → USE	0.550	.564	9.95	0.441–0.658	< .001	Supported
PE → BI → USE	0.267	.253	5.86	0.178–0.356	< .001	Significant indirect
EE → BI → USE	0.127	.116	3.39	0.054–0.201	< .001	Significant indirect
SI → BI → USE	0.146	.133	3.81	0.071–0.221	< .001	Significant indirect

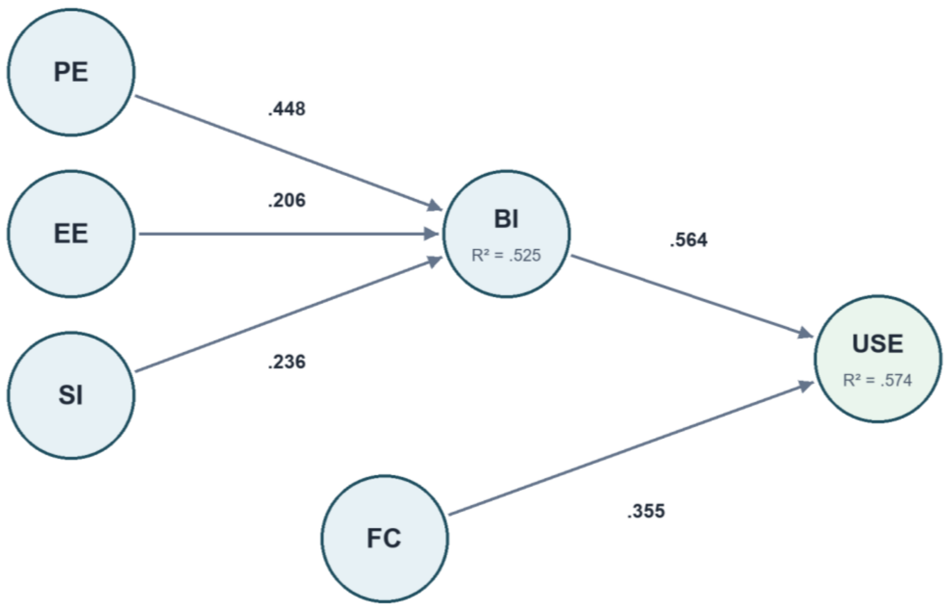
Note. B = unstandardized estimate. β = standardized estimate. CI = robust 95% confidence interval. R^2(BI) = .525; R^2(USE) = .574.

Performance expectancy had the largest association with behavioral intention (β = .448), followed by social influence (β = .236) and effort expectancy (β = .206). Behavioral intention had the largest association with self-reported use (β = .564), while facilitating conditions were also positively associated with self-reported use (β = .355). The model explained 52.5% of the variance in behavioral intention and 57.4% of the variance in self-reported use. PE, EE, and SI also had significant indirect associations with self-reported use through behavioral intention

Figure 3 displays the standardized structural equation model. It presents the six latent constructs and the five hypothesized paths; indicators, residuals, and covariance values are omitted for visual clarity. The displayed path coefficients correspond with Table 7.

Figure 3

Standardized Structural Equation Model



Note. Values are standardized estimates. Covariances among exogenous latent constructs were estimated but are omitted, together with indicators, residual terms, and nonsubstantive fixed parameters, for visual clarity. All displayed path values correspond with Table 7.

4. Discussion

4.1. Discussion of Factors Associated With Behavioral Intention (H1–H3)

The structural model supported all three hypothesized associations with behavioral intention.

Taken together, the findings indicate that teachers' intention to use AI in autism education was associated with perceived instructional value, ease of use, and the social context surrounding adoption. This pattern is consistent with the core UTAUT proposition that teachers' intentions are shaped by expected benefits, ease of use, and social influence (Kittinger & Law, 2024; Venkatesh et al., 2003).

The positive associations of performance expectancy, effort expectancy, and social influence are broadly consistent with recent Saudi UTAUT-based evidence from university students (Alshammari et al., 2026). However, the relative strength of these associations differs across student and teacher populations and educational settings. The comparison should therefore be read as evidence of contextual variation rather than as a direct replication.

Performance expectancy had the largest association with behavioral intention. This suggests that teachers were more likely to report an intention to use AI when they expected it to support relevant teaching activities, such as adapting materials, monitoring progress, or planning instruction. The result should be understood as a perception of instructional value rather than evidence that AI improved learner outcomes. It is nevertheless consistent with teacher-AI studies in which perceived usefulness or expected performance benefit was related to intention, including research with Greek teachers and wider teacher-adoption reviews (Velli & Zafiropoulos, 2024; Xue et al., 2025).

A recent Saudi study of university students did not report a significant association for its performance-related construct and intention to adopt AI (Alshammari et al., 2025). That study used different constructs, measures, participants, and educational settings from the present UTAUT model. The contrast therefore indicates contextual variation rather than a direct contradiction of the performance expectancy finding.

Social influence also showed a significant positive association with behavioral intention. The result suggests that teachers' intentions were related, in part, to how AI use was viewed within their professional setting. Leadership endorsement, peer support, and professional norms were not measured as separate variables in this study. They should therefore be treated as possible explanations and practical implications rather than direct findings. However, the result is consistent with UTAUT and with recent teacher-AI research showing that social and organizational context can remain relevant when educators consider new technologies (Ateş & Polat, 2025; Venkatesh et al., 2003; Zraydi et al., 2026).

Effort expectancy was also associated with behavioral intention. Ease of learning and use was therefore related to teachers' behavioral intention, even though perceived instructional value was more strongly associated with intention in this model. This distinction matters in autism education, where a tool may be seen as useful but still need to fit everyday teaching routines. Existing research similarly identifies effort expectancy as relevant to teacher AI adoption, although its relative importance varies across technologies, populations, and educational settings (Acquah et al., 2024; Kittinger & Law, 2024; Xue et al., 2025).

The relative ordering of the three associations should not be treated as universal. It describes the present sample and the specified model rather than a fixed hierarchy for all teachers or AI tools. For example, the recent UAE study of teachers working with students with learning disabilities found a different pattern of significant associations (Zraydi et al., 2026). The present findings therefore support H1–H3, but they remain limited to teachers' reported perceptions and intention at one period of data collection.

4.2. Discussion of Factors Associated With Self-Reported Use (H4–H5)

Behavioral intention was positively associated with self-reported use, supporting H5. This result is consistent with UTAUT, which treats intention as closely related to technology use (Venkatesh et al., 2003). Behavioral intention used agreement statements about intended use, whereas USE measured reported frequency during the previous four weeks. Their descriptive means should therefore not be directly compared. Within this sample, higher behavioral intention was associated with more frequent self-reported AI use.

Facilitating conditions were also positively associated with self-reported use, supporting H4. The items captured access to necessary devices and software, technical support, and adequate training. Taken together, the results suggest that these enabling conditions were related to self-reported use within this sample. They should not be read as proof of a national implementation failure, but they do identify an institutional dimension that warrants attention in autism-education settings.

The FC-to-USE association differs from the nonsignificant facilitating-conditions finding in a Jordanian study of green-AI behavior (Alkhwaldi et al., 2026). The studies involve different populations, behaviors, institutional settings, and forms of AI use. This variation suggests that facilitating conditions may be more salient when self-reported use depends on school infrastructure, training, and technical support, but the present cross-sectional data do not establish why the associations differ.

The interpretation of facilitating conditions is supported by related Saudi special-education evidence. Alhaif et al. (2025) reported that special-education teachers recognized the importance of AI applications and related obstacles, while their reported knowledge and skill were neutral. Alnaim and Al-Otaibi (2025) likewise identified training and digital-infrastructure barriers to AI application use among teachers of students with learning disabilities in Saudi Arabia. A broader Saudi review also highlights the relevance of teacher capacity and infrastructure to technology integration for learners with disabilities (Hamid et al., 2025). These studies do not establish the same relationships as the present SEM, but they provide relevant context for interpreting the FC-USE association.

Taken together, these findings indicate that AI adoption in this context involves both individual readiness to use the technology and the conditions that support its practical integration. In autism education, practical support should remain sensitive to the need for tools that fit individual learners, teaching goals, and classroom routines. Reviews of AI in special education and autism intervention research similarly emphasize the diversity of applications and the need for careful, learner-centered implementation (Hussein et al., 2025; Kotsi et al., 2025). This interpretation remains cautious because the study did not directly assess school policies, tool quality, or observed classroom practice.

4.3. Indirect Associations through Behavioral Intention

The indirect associations further indicate the role of behavioral intention in the specified model. Performance expectancy, social influence, and effort expectancy were indirectly associated with self-reported use through behavioral intention. This pattern is consistent with behavioral intention linking teachers' perceptions and their self-reported use within the cross-sectional model. It should not be treated as evidence of causal mediation or as proof that changing one construct would necessarily change technology use over time (Nikolic et al., 2024; Venkatesh et al., 2003).

4.4. Theoretical Implications

This study has three bounded theoretical implications for the use of UTAUT in AI adoption. First, the findings support the empirical distinction between future-oriented behavioral intention and recent self-reported use within the same model. Behavioral intention captured intended future AI use, whereas USE captured the reported frequency of specific teaching activities during the previous four weeks. Their empirical distinction supports the value of examining intention and recent use as related but separate constructs in educational technology research (Kittinger & Law, 2024). This interpretation remains limited by the cross-sectional design and does not establish temporal order or causation.

Second, the structural pattern is consistent with UTAUT's distinction between factors associated with intention and the enabling conditions associated with technology use (Venkatesh et al., 2003). This distinction is particularly relevant in autism education, where implementation may depend on access, technical support, practical training, and the ability to integrate tools into specialized classroom routines. The findings therefore support the continued theoretical relevance of facilitating conditions alongside intention-related perceptions in this educational context. They do not, however, establish facilitating conditions as a causal boundary condition or moderator.

Third, the findings reinforce the view that UTAUT relationships should be interpreted in relation to the professional and institutional context in which technology adoption occurs. Recent studies have reported different patterns across student and teacher populations and educational settings (Alshammari et al., 2026; Zraydi et al., 2026). This variation is consistent with teacher-adoption evidence showing that UTAUT relationships may differ according to the technology, professional role, and institutional context (Kittinger & Law, 2024). The contribution of the present study is therefore not a new UTAUT model, but evidence of how established UTAUT relationships operate among special-education teachers working in autism education in Saudi Arabia.

5. Limitations

This study used a cross-sectional design, so the findings represent teachers' perceptions, behavioral intention, and self-reported AI use at one period of data collection. The relationships among PE, EE, SI, FC, BI, and USE should therefore be interpreted as associations within the study sample. They do not establish causal direction, temporal order, or causal mediation through behavioral intention. Longitudinal research, including measurements before and after training or implementation support, would provide stronger evidence about how these relationships develop over time.

The study also relied on single-source self-reported questionnaire data. In particular, USE represented teachers' self-reported use rather than objective system logs, observational records, or platform analytics. The self-reported level of AI use should therefore be understood as perceived classroom practice, not directly observed behavior. Collecting all core constructs from the same respondents at one point in time also means that shared method variance and socially desirable responding cannot be ruled out completely. Future studies could combine survey responses with usage records, classroom observation, or school-level implementation data.

A further limitation concerns the purposive convenience sampling strategy and the absence of a calculable response rate. The survey was distributed through school and professional communication channels, but the total number of eligible teachers who received the invitation could not be determined. The sample may therefore underrepresent teachers who were less active in these networks, less comfortable with online questionnaires, or less interested in AI-related issues. Non-response bias could not be assessed directly, and the findings should not be treated as fully representative of all special-education teachers working in autism education in Saudi Arabia.

The questionnaire was adapted to the context of AI use in autism education. The CFA provided evidence consistent with the intended six-factor structure, and the standardized loadings, reliability estimates, AVE, and HTMT values supported measurement quality within this sample. However, this does not amount to complete validation for all teacher populations or educational settings. The broad definition of AI tools also means that participants may have referred to different applications or technologies when reporting their perceptions and self-reported use, which may have introduced some heterogeneity in their responses. In addition, although the Arabic administration and English presentation were aligned to retain the intended construct meanings, the study did not include a formal forward–back translation or separate language-validation procedure. The study did not include a separate validation sample, test-retest evidence, criterion-related validation, or tests of measurement invariance across teacher groups. Replication with independent and more diverse samples is therefore needed before the measurement findings are generalized more broadly.

6. Recommendations

The first recommendation is to make the practical instructional value of AI tools visible to teachers. Professional development should use teaching examples that are directly relevant to autism education, such as adapting materials, supporting differentiated instruction, monitoring progress, or preparing instructional activities.

The second recommendation is to strengthen the practical conditions that support sustained use. Schools should review teachers' access to suitable devices and software, technical assistance, and training that can be applied in classroom practice.

The third recommendation concerns the professional environment surrounding adoption. Social influence was positively associated with behavioral intention, although leadership endorsement, collegial support, and professional norms were not measured as separate variables in this study. Schools may therefore consider clear guidance, opportunities for peer exchange, and supervised opportunities to discuss appropriate AI use. These steps should be viewed as practical implications of the social influence finding rather than as effects directly tested in the model. Any school-level initiative should also address safe, learner-centered, and context-appropriate use in autism classrooms.

Practical preparation should also be accompanied by clear guidance on appropriate, responsible, and ethical educational use. This is consistent with Saudi student evidence linking readiness and ethical awareness with AI-adoption intention, although those relationships were not measured separately among the special-education teachers in the present study (Alshammari et al., 2025).

Future research should examine whether the identified associations remain stable across time and across different school contexts. Longitudinal designs could assess change before and after focused support, while objective usage records or classroom observation could complement teachers' self-reported use. Broader sampling strategies and independent validation samples would also improve generalizability. Further measurement work should examine whether the six-factor instrument operates similarly across relevant groups, such as levels of teaching experience and educational qualification.

7. Conclusion

This study used UTAUT to examine factors associated with special-education teachers' behavioral intention and self-reported use of AI tools in autism education in Saudi Arabia. The six-factor measurement model showed satisfactory reliability and validity within the study sample. The structural model supported all five hypothesized positive associations. Performance expectancy had the largest association with behavioral intention ($\beta = .448$), while behavioral intention had the largest association with self-reported use ($\beta = .564$). Facilitating conditions were also positively associated with self-reported use ($\beta = .355$).

Behavioral intention was rated relatively highly, whereas facilitating conditions had the lowest descriptive mean. This pattern, together with the FC-USE association, suggests that teachers' self-reported use was related not only to their intention but also to practical conditions that may enable classroom use. However, the study did not observe classroom behavior, assess the quality of individual AI tools, or test school policies directly. The findings should therefore not be read as evidence that teachers' intentions cause use or that one institutional intervention would resolve implementation challenges.

At a theoretical level, the study provides bounded evidence that the UTAUT distinction between intention formation and use-related enabling conditions remains meaningful in this specialized setting. It empirically separates future behavioral intention from recent self-reported use, while performance expectancy, effort expectancy, and social influence were associated with behavioral intention and facilitating conditions were separately associated with self-reported use. The relative strength of the intention-related paths should be interpreted as context dependent rather than universal. These findings do not create a new theory, establish temporal or causal mechanisms, or extend UTAUT with new constructs. They strengthen the empirical application of UTAUT to AI adoption in autism education within the present sample.

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

Declaration of interest: The author declares that they have no conflict of interest regarding the publication of this paper.

Ethical statement: This study was approved by the Research Ethics Committee of Najran University, Saudi Arabia, with Approval No. 202512-076-039808-087015 on December 16, 2025.

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Appendix 1. Research Instrument: Teachers' Adoption of Artificial Intelligence in Autism Education (UTAUT Model)

Section (A): Demographic Information
1. Gender (Male / Female)
2. Age Group (Under 30 / 30–39 / 40–49 / 50 and above)
3. Educational Qualification (Bachelor / Diploma / Master / PhD)
4. Teaching Experience (Less than 5 years / 5–10 / 11–15 / 16+ years)

Section (B): UTAUT Constructs

Response scale for PE, EE, SI, FC, and BI: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Response scale for Self-reported Use (USE): During the past four weeks, 1 = Never, 2 = Once, 3 = Two or three times, 4 = Weekly, 5 = Several times per week

Language and item basis. The questionnaire was administered in Arabic, and the Appendix 1 presents the corresponding English wording for reporting purposes. The Arabic and English versions were aligned to preserve the intended construct meanings and contextualized teaching-task content. The PE, EE, SI, FC, and BI item sets were grounded in UTAUT. Some items retained close correspondence with established UTAUT measurement content, whereas others were contextually specified for AI-supported teaching in autism education. USE1–USE3 were developed specifically for this study as task-based indicators of self-reported AI use during the previous four weeks. The instrument is therefore presented as a contextually developed UTAUT-based measure rather than as a previously validated fixed 25-item scale. No formal translation-validation procedure is claimed.

Performance Expectancy (PE)

Code	Item (English)
PE1	Using AI tools improves the quality of teaching for students with autism.
PE2	AI applications help me provide more personalized learning experiences.
PE3	AI-supported instruction increases student engagement and motivation.
PE4	AI tools can help me monitor students' progress and identify areas where additional support is needed.
PE5	Using AI tools helps me achieve my instructional goals for students with ASD more effectively.

Effort Expectancy (EE)

Code	Item (English)
EE1	Learning to use AI tools for ASD-related teaching tasks would be easy for me.
EE2	I find AI applications clear and simple to operate for teaching tasks.
EE3	I can quickly become skilled at using AI tools for teaching tasks.
EE4	Using AI tools would not seriously disrupt my usual lesson-preparation routines.
EE5	Overall, AI technologies are user-friendly for teaching students with ASD.

Social Influence (SI)

Code	Item (English)
SI1	My school leaders encourage teachers to use AI tools when they are educationally appropriate.
SI2	Special-education supervisors or coordinators support appropriate AI use in ASD education.
SI3	Colleagues whose professional judgment I trust view responsible AI use as acceptable in ASD teaching.
SI4	In my school, responsible AI use is becoming a professionally accepted practice.

Facilitating Conditions (FC)

Code	Item (English)
FC1	I have reliable internet and device access needed to use AI tools for teaching tasks.
FC2	My school provides or permits access to AI tools that can be used for instructional preparation.
FC3	Technical support is available when I face problems using AI tools for teaching.
FC4	I have received practical training on how to use AI tools in special-education teaching tasks.

Behavioral Intention (BI)

Code	Item (English)
BI1	I intend to use AI tools in autism education during the next semester.
BI2	I plan to use AI tools to support lesson preparation for students with ASD during the next semester.
BI3	I intend to use AI tools to adapt activities or materials for individual students with ASD.
BI4	I expect to use AI tools regularly in my ASD-related teaching in the near future.

Self-Reported Use (USE)

Code	Item (English)
USE1	In the past four weeks, how often did you use AI tools to prepare learning materials for students with ASD?
USE2	In the past four weeks, how often did you use AI tools to adapt activities to individualized education plan (IEP) goals or learner profiles?
USE3	In the past four weeks, how often did you use AI tools to create visual supports, prompts, communication supports, or social-story-style materials?