Current Psychology (2026) 45:1665
https://doi.org/10.1007/s12144-026-10207-4

Development of a digital transformation readiness scale in education: a data mining-based analysis of scale dimensions

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Received: 12 October 2025 / Accepted: 15 October 2026
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Abstract

This methodological scale-development study had two sequential aims: (1) to develop and validate the Educational Digital Transformation Readiness Scale (EDTRS) for university students and (2) to explore heterogeneity in the empirically derived readiness profiles using data-mining methods. A separate pilot study (n = 25) preceded the main study. The main sample comprised 460 fourth-year students from a state university; 260 students were included in exploratory factor analysis (EFA) and reliability analyses and an independent group of 200 students in confirmatory factor analysis (CFA). The final EDTRS contained 19 items and two subdimensions, Behavioral Attitude and Affective Attitude, which explained 66.4% of the total variance. Cronbach's alpha and McDonald's omega for the total scale were .945 and .959, respectively. Cluster analysis identified two profiles characterized by relatively lower and higher scores on both attitudinal dimensions. CHAID produced the lowest observed decision-tree error rate (.401), compared with a majority-class baseline error of .437, and identified perceived readiness of the education system as the first differentiating characteristic; gender and self-rated knowledge differentiated subsequent branches. The EDTRS should therefore be interpreted as a measure of students' attitudinal readiness for digital transformation rather than as a direct test of digital knowledge or skills. The combined psychometric and exploratory profiling approach may support more targeted, context-sensitive digital transformation initiatives in higher education.

Keywords Digital transformation readiness · Higher education · Behavioral attitude · Affective attitude · Scale development · CHAID

Introduction

Digital transformation in higher education is a socio-technical change process rather than the simple digitization of existing practices. It involves the integration of digital technologies with changes in teaching and learning, institutional processes, organizational capabilities, infrastructure, and the roles of students and educators. Accordingly, the educational value of digital transformation depends not only on access to technology but also on whether institutions and learners are prepared to engage meaningfully with changing digital environments (Benavides et al., 2020; Chounta et al., 2024).

For students, digitally transformed learning environments can expand flexibility, access to resources, feedback, collaboration, and opportunities for personalized learning. At the same time, greater technological availability does not guarantee equivalent preparedness. Students differ in their prior exposure, confidence, attitudes, self-regulatory

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Published online: 28 October 2026

capacity, perceived support, and opportunities to use technology. These differences may be amplified when accessibility, usability, and inclusion are unevenly distributed across digital learning environments (Händel et al., 2022; Heilala et al., 2026; Kinnula et al., 2021).

Theoretical framework and construct definition

Digital transformation readiness is conceptually adjacent to, but distinct from, digital competence, digital literacy, technology acceptance, self-efficacy, and institutional digital readiness. Digital competence primarily concerns the knowledge and skills required to use digital technologies safely, critically, and effectively. Recent psychometric work with higher education students has operationalized digital competence through domains such as access to and management of digital content, digital content creation, communication, security, and digital empathy (Mejías-Acosta et al., 2024). Digital literacy likewise emphasizes the capacity to access, evaluate, create, and communicate information in digital environments. These constructs are competence-oriented and should not be treated as synonymous with a learner's readiness to participate in a broader process of educational transformation.

Other adjacent constructs address different psychological mechanisms. Technology acceptance focuses on intended or actual technology use and is commonly explained through beliefs such as perceived usefulness and perceived ease of use (Davis, 1989); it does not, by itself, represent preparedness for a broader process of educational transformation. Technology-related self-efficacy reflects confidence in one's capability to use a technology; for example, the GSE-6AI measures self-efficacy specifically in the use of artificial intelligence among university students (Morales-García et al., 2024). Self-regulated and self-directed learning concern learners' capacity to plan, monitor, regulate, and sustain their own learning; recent evidence indicates that these capacities are important in AI-supported and digitally mediated learning and therefore represent dimensions of preparedness that cannot be reduced to attitude alone (Achuthan, 2025). Technology adoption and diffusion perspectives add a further contextual layer by emphasizing trialability, perceived relevance, engagement, and social or organizational structures through which innovations become normalized in educational practice (Achuthan et al., 2020).

Readiness also operates at more than one level. At the institutional level, digital readiness includes organizational strategy, infrastructure, governance, support, and data-informed indicators of capacity for digital transformation (Chounta et al., 2024). At the student level, the present study focuses more narrowly on attitudinal readiness: students' behavioral and affective orientations toward engaging with digital transformation in education. This interpretation is consistent with the tripartite model of attitude, which distinguishes affective, behavioral, and cognitive components, and with recent work showing that students' attitudes toward digitalization are shaped by access, prior exposure, gender, and contextual conditions (Alam et al., 2023; Breckler, 1984). Thus, the EDTRS is positioned as an attitudinal readiness instrument rather than as a comprehensive digital competence test, a self-efficacy scale, or a measure of institutional readiness.

The initial conceptual rationale framed readiness broadly in terms of knowledge, skills, and attitudes. However, the scale-development documentation did not include a formal a priori assignment of each draft item to mutually exclusive knowledge-, skill-, or attitude-specific subscales. A retrospective item-domain map was therefore not imposed. Instead, construct interpretation follows the empirical factor solution, which yielded two attitudinal dimensions rather than separate knowledge, skill, and attitude factors. The contribution of the EDTRS is consequently framed more precisely as a student-focused measure of attitudinal readiness for digital transformation in education and, after psychometric validation, as a basis for exploratory profiling of readiness heterogeneity (Bhutto et al., 2025; Mejías-Acosta et al., 2024).

Method

Aim and research questions

The primary aim was to develop and evaluate the validity and reliability of the EDTRS. A secondary, exploratory aim was to profile heterogeneity in the empirically derived scale dimensions using cluster analysis and decision-tree methods. The data-mining phase was conducted after psychometric validation and was intended to extend interpretation of the validated scale, not to serve as additional evidence of construct validity.

> Research Question 1: Does the EDTRS demonstrate adequate validity and reliability for assessing university students' attitudinal readiness for digital transformation in education?
> Research Question 2: What student readiness profiles emerge from the validated EDTRS dimensions, and which measured demographic or perception-based characteristics differentiate those profiles in exploratory decision-tree analysis?

Study design

The study was designed as a methodological scale-development study followed by a secondary exploratory data-mining phase.

Population and sample

The population consisted of all fourth-year students (N = 2,769) enrolled in the faculties of a state university in Istanbul, Türkiye.

For scale-development studies, sample-size recommendations commonly relate the number of participants to the number of candidate items. A participant-to-item ratio of approximately 10:1 was targeted. The main study included 460 students: 260 students were used for EFA and reliability analyses, and an independent group of 200 students was used for CFA (Cappelleri et al., 2013). The separate pilot sample (n = 25) was not included in the main sample.

The number of students to be included from each faculty was determined using stratified sampling. Within the strata, students who met the study criteria and voluntarily agreed to participate were selected using random sampling.

Data collection tools and scale-development procedure

An Information Form and the draft EDTRS were used for data collection. The Information Form contained six questions addressing descriptive characteristics and perceptions related to digital transformation. Variables subsequently selected by the CHAID (Chi-squared Automatic Interaction Detection), model included gender, perceived readiness of the education system for digital transformation, and self-rated knowledge of digital transformation. These variables represent different types and levels of measurement and were therefore treated as exploratory covariates rather than equivalent-precision psychometric indicators.

The EDTRS was developed through four sequential stages: (1) literature review and item generation, (2) expert review and content validity, (3) pilot testing and item screening, and (4) main-sample psychometric validation followed by exploratory data-mining analyses.

Stage 1—Item generation. The researchers reviewed national and international literature on digitalization, digital transformation, digital competence, digital literacy, technology readiness, and student readiness, producing a 32-item draft instrument intended to reflect students' readiness for digital transformation in education. The scale-development documentation did not record a formal item-by-item assignment to mutually exclusive knowledge-, skill-, and attitude-specific subscales. Accordingly, the present report does not retrospectively impose a domain classification that was not documented in the original development procedure.

The 32-item draft instrument used the same five response categories that were retained in the final scale: (1) Never, (2) Rarely, (3) Occasionally, (4) Frequently, and (5) Always.

Stage 2—Expert review and content validity. Eight experts evaluated the 32-item draft scale for content coverage and comprehensibility. Expert opinions were obtained using an Expert Opinion Form, and the Davis technique was used to calculate the content validity index (Karakoç & Dönmez, 2014; Tavşancıl, 2005; Yurdugül, 2005). No item had a content validity index below.75; therefore, no item was removed at this stage. Wording and expression were revised in line with expert feedback.

Stage 3—Pilot testing. A pilot study was conducted with 25 fourth-year students from the faculties in which the main study would be conducted. The pilot examined comprehensibility, usability, and suitability for the target population. Pilot participants were excluded from the main sample. Corrected item-total correlations and changes in Cronbach's alpha if an item was deleted were examined. Six items (M1, M3, M4, M10, M14, and M15) with negative corrected item-total correlations were removed, yielding a 26-item form. For the 26-item pilot version, Cronbach's alpha was.930 and the reported Guttman lambda coefficients ranged from.852 to.941. Given the small pilot sample, these coefficients were used only as preliminary item-screening evidence rather than definitive reliability estimates.

Stage 4—Main-sample validation and exploratory profiling. The 26-item form was administered in the main study. Psychometric validation was performed using the EFA/reliability sample (n = 260) and the independent CFA sample (n = 200). After the factor structure was established, the validated subdimension scores for the full main sample (N = 460) were examined using cluster analysis and decision-tree algorithms to identify readiness profiles and characteristics that differentiated those profiles.

The complete sequence of scale development, psychometric validation, and data-mining-based profiling is summarized in Fig. 1.

Data analysis

Descriptive statistics, EFA, CFA, and internal-consistency analyses were conducted. EFA was used to determine the empirical structure of the EDTRS, and Horn's parallel analysis was used to inform the number of factors retained. Varimax rotation and principal component extraction were applied, and a polychoric correlation matrix was used because the items were ordinal Likert-type variables (Holgado-Tello et al., 2010). CFA was conducted using diagonally weighted least squares (DWLS). Cronbach's alpha and McDonald's omega were calculated for the total scale and each subdimension. Statistical significance was evaluated at $p < .05$. Psychometric analyses were conducted in R (R Core Team, 2023) using the psych (Revelle, 2018) and lavaan (Rosseel, 2012) packages.

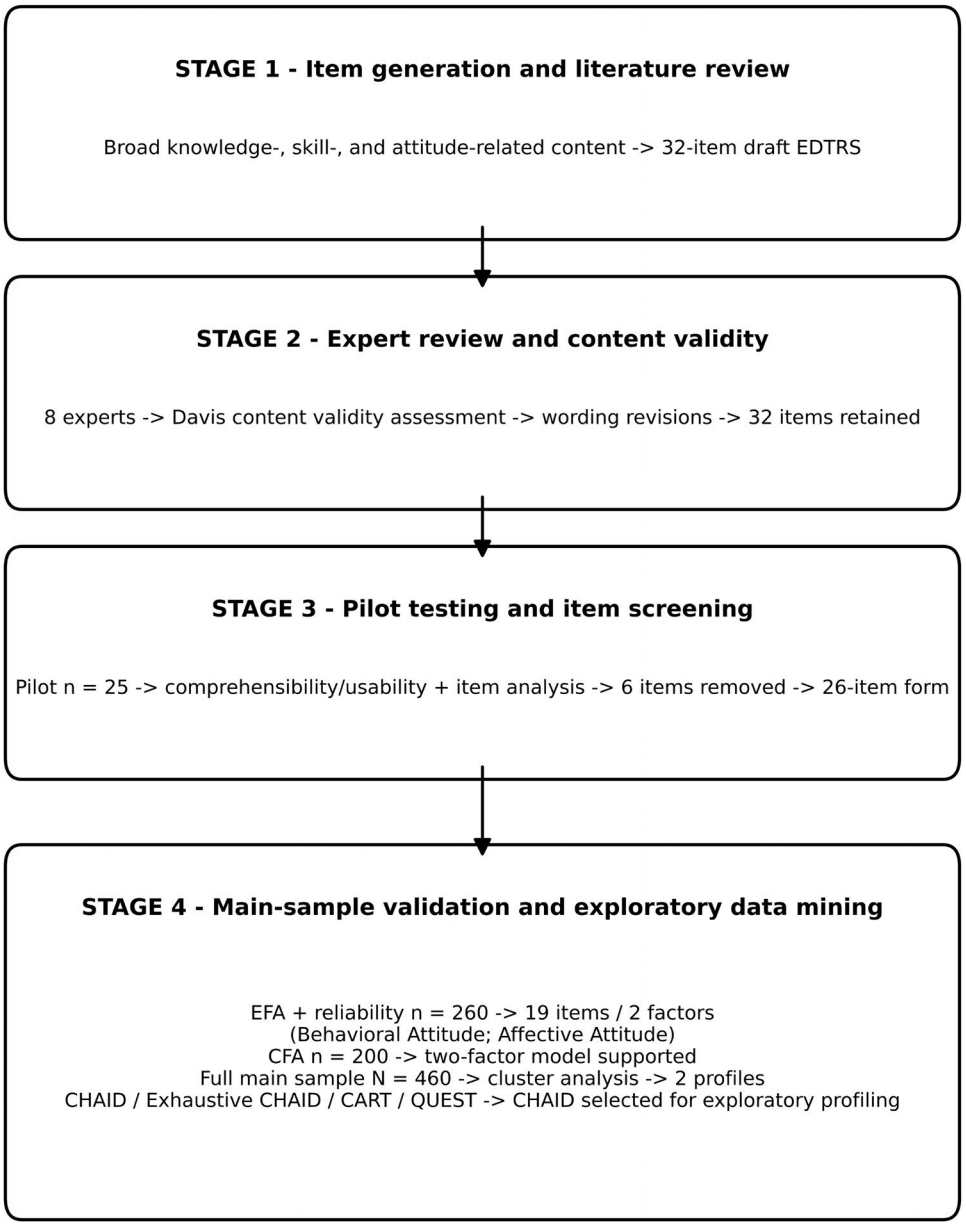

Fig. 1 Study design and data-mining flowchart

After psychometric validation, Behavioral Attitude and Affective Attitude scores were analyzed using data-mining methods. Cluster analysis was first applied to the two validated subdimension scores and yielded a two-cluster solution representing relatively lower and relatively higher attitudinal-readiness profiles. The archived revision materials document the use of cluster analysis and the resulting two-cluster solution, but do not identify the specific clustering algorithm or its tuning parameters; therefore, no undocumented clustering specification is inferred in this report. Cluster membership was then treated as the dependent variable in CHAID Exhaustive CHAID, CART (Classification and Regression Trees), and QUEST models. Candidate predictors were drawn from the descriptive and perception-based variables collected with the Information Form because these variables represented available individual and contextual characteristics plausibly related to digital readiness. The algorithm selected the variables that generated the most informative splits. Error rates were compared across algorithms, and CHAID was retained because it had the lowest observed error rate. The tree was interpreted as an exploratory classification model; no causal interpretation was made.

Use of generative AI-assisted tools during revision

During manuscript revision, ChatGPT (OpenAI) was used to support language editing, organization, and drafting of revisions in response to reviewer comments. It

was not used to generate or alter research data, perform statistical analyses, or make independent scientific decisions. All AI-assisted text was critically reviewed against the authors' original materials and cited sources, revised where necessary, and approved by the authors, who retain full responsibility for the scientific content and final manuscript.

Results

The mean age of the students was 22.0 ± 1.34 years; 55% were female, 60% were graduates of Anatolian high schools, and 15% were graduates of science high schools. Overall, 32% of the students thought that Türkiye's education system was ready for digital transformation, whereas 69% believed that university students were ready for digital transformation in education. The mean self-rated knowledge score for digital transformation was 5.98 ± 2.35.

Validity and reliability analysis of the EDTRS

The Kaiser–Meyer–Olkin measure was.922, and Bartlett's test of sphericity was statistically significant ($\chi^2 = 3936.372$, df = 171, $p < .05$), supporting the suitability of the inter-item correlation matrix for factor analysis.

EFA was conducted on the 26-item form. Items 1, 2, 5, 11, and 16 were removed because of cross-loading based on a factor-loading difference below.20, and items 3 and 15 were removed because their factor loadings were below.40. The final analysis yielded a 19-item, two-factor structure with factor loadings above.40 and communalities above.30 (Table 1). Parallel analysis supported retention of two factors, and the final solution explained 66.4% of the total variance.

Cronbach's alpha was.945 and McDonald's omega was.959 for the total EDTRS. For Behavioral Attitude, Cronbach's alpha was.924 and McDonald's omega was.944; for Affective Attitude, the corresponding coefficients were.914 and.941. Corrected item-total correlations were positive, and deleting individual items did not meaningfully increase reliability; therefore, no additional items were removed at this stage (Table 2).

The two factors were named according to the content of the retained items. Factor 1 was labeled Behavioral Attitude and Factor 2 was labeled Affective Attitude. CFA in the independent sample supported the two-factor structure; all standardized item loadings were positive and statistically significant ($p < .05$) (Table 2, Fig. 2).

The reported CFA fit indices were $\chi^2/df = 0.969$, GFI = .978, CFI = 1.000, AGFI = .972, TLI = 1.000, IFI = 1.000, and RMSEA = .000.

Table 1 Factor loadings and communalities of the EDTRS items according to EFA results

Item	Behavioral Attitude (F1)	Affective Attitude (F2)	Communality
EDTRS24	.799		.761
EDTRS25	.781		.723
EDTRS21	.780		.689
EDTRS19	.764		.696
EDTRS18	.749		.656
EDTRS26	.737		.691
EDTRS17	.723		.633
EDTRS20	.714		.635
EDTRS23	.704		.641
EDTRS22	.629		.523
EDTRS7		.842	.795
EDTRS8		.832	.784
EDTRS9		.821	.790
EDTRS6		.774	.692
EDTRS4		.725	.656
EDTRS12		.723	.610
EDTRS13		.675	.573
EDTRS14		.643	.575
EDTRS10		.622	.505

Knowledge-, skill-, and attitude-related content informed item generation, but items were not assigned to fixed a priori *subscales. The table therefore reports the empirical factor allocation of retained draft-item identifiers. In the finalized scoring form, Items 1–9 constitute Affective Attitude and Items 10–19 constitute Behavioral Attitude*

Scoring of the scale

The 19 EDTRS items are scored on a five-point Likert scale: (5) Always, (4) Frequently, (3) Occasionally, (2) Rarely, and (1) Never. For the finalized scoring form, the retained items are consecutively renumbered: Items 1–9 constitute Affective Attitude and Items 10–19 constitute Behavioral Attitude. Higher scores indicate greater attitudinal readiness for digital transformation in education as represented by the Behavioral Attitude and Affective Attitude dimensions. The EDTRS does not provide a direct performance-based measure of digital knowledge or skills.

Analysis of EDTRS subdimensions using data-mining methods

Cluster analysis of Behavioral Attitude and Affective Attitude scores yielded two profiles. Students in Cluster 1 had relatively lower mean scores on both dimensions than students in Cluster 2; therefore, the clusters are described as relatively lower and relatively higher attitudinal-readiness profiles rather than absolute categories of readiness (Table 3).

CHAID had the lowest observed error rate (.401), followed by Exhaustive CHAID (.425), QUEST (.434), and CART (.438) (Table 4). Because Cluster 1 contained 259 of

Table 2 Reliability analysis results and standardized CFA loading statistics of the EDTRS

Dimension	Item	Corrected item-total correlation	MSA	Cronbach alpha	McDonald omega	Standardized CFA loading	p
Behavioral Attitude	EDTRS24	.805	.914	.924	.944	.598	-
	EDTRS25	.784	.914			.633	<.001
	EDTRS21	.759	.915			.642	<.001
	EDTRS19	.787	.914			.626	<.001
	EDTRS18	.757	.916			.513	<.001
	EDTRS26	.764	.915			.700	<.001
	EDTRS17	.725	.917			.529	<.001
	EDTRS20	.724	.918			.681	<.001
	EDTRS23	.733	.917			.665	<.001
	EDTRS22	.621	.922			.542	<.001
Affective Attitude	EDTRS7	.831	.899	.914	.941	.524	-
	EDTRS8	.805	.902			.580	<.001
	EDTRS9	.831	.898			.572	<.001
	EDTRS6	.761	.904			.540	<.001
	EDTRS4	.738	.904			.480	<.001
	EDTRS12	.704	.906			.570	<.001
	EDTRS13	.714	.906			.706	<.001
	EDTRS14	.706	.907			.785	<.001
	EDTRS10	.622	.912			.631	<.001

Total-scale Cronbach's alpha=.945 and McDonald's omega=.959. MSA=measure of sampling adequacy; CFA=confirmatory factor analysis

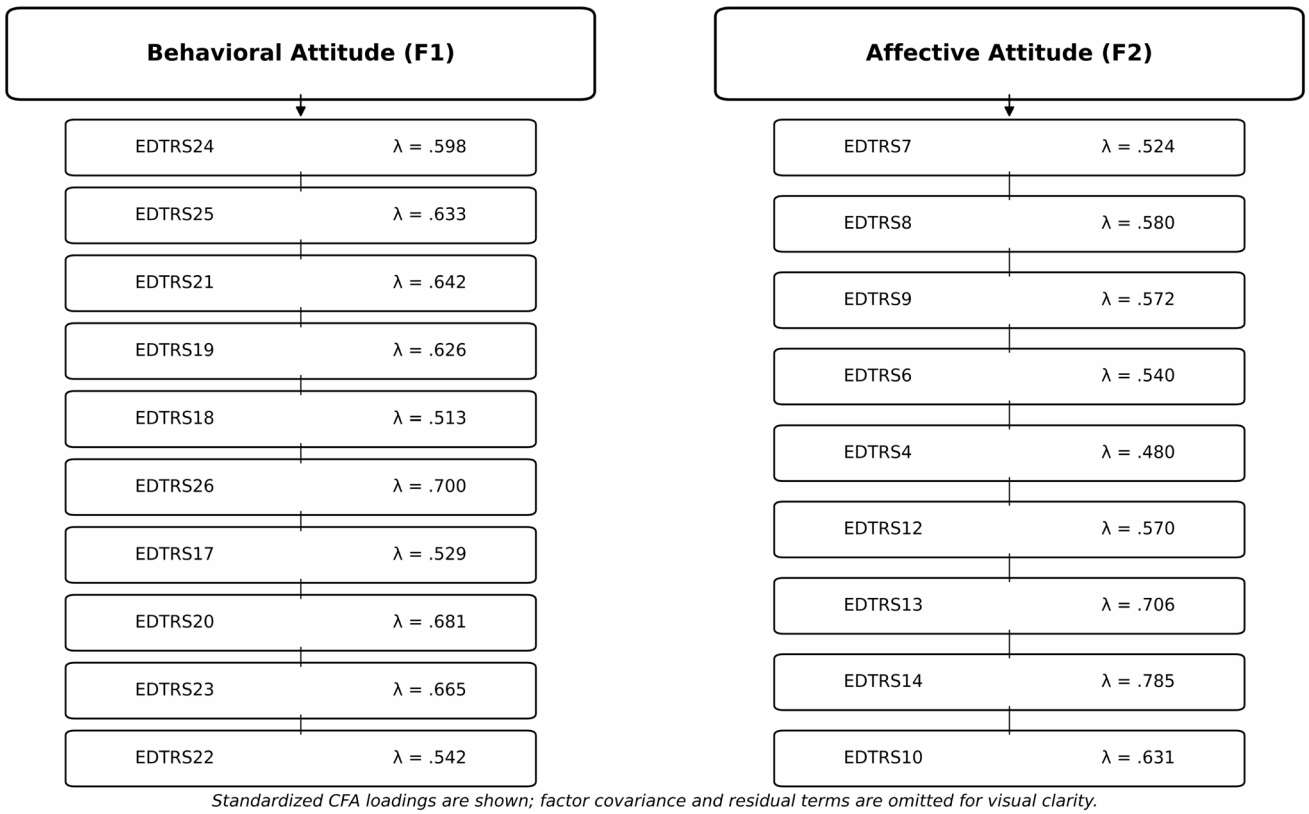

Fig. 2 CFA model of the two-factor EDTRS; standardized factor loadings are shown

Table 3 Clustering results for the EDTRS subdimensions

Subdimension	Cluster 1 ($n=259$)			Cluster 2 ($n=201$)		
	Mean ± SD	**Min**	**Max**	**Mean ± SD**	**Min**	**Max**
Behavioral Attitude	40.981 ± 5.536	24	48	43.099 ± 7.145	25	50
Affective Attitude	37.023 ± 4.945	22	45	39.495 ± 6.425	18	45

Cluster 1 and Cluster 2 represent relatively lower and relatively higher attitudinal-readiness profiles, respectively; they are not absolute diagnostic categories

Table 4 Comparison of decision-tree algorithms for classifying cluster membership

Model	Error rate	Accuracy	Selected model	Characteristics retained in final CHAID tree
CHAID	.401	.599	CHAID	Perceived readiness of education system; gender; self-rated knowledge
Exhaustive CHAID	.425	.575		
CART	.438	.562		
QUEST	.434	.566		
Majority-class baseline	.437	.563	Reference	Always predict Cluster 1 (259/460 = 56.3%)

Accuracy = 1—error rate. The CHAID accuracy (.599) was 3.6 percentage points higher than the majority-class baseline accuracy (.563); this modest improvement is interpreted exploratorily

460 students (56.3%) and Cluster 2 contained 201 (43.7%), a classifier that assigned every student to the majority class would have an error rate of.437 and an accuracy of.563. Thus, the CHAID error rate corresponds to an accuracy of.599, an absolute improvement of 3.6 percentage points over the majority-class baseline. This improvement is modest and is interpreted as exploratory rather than as evidence of strong predictive performance.

The CHAID tree identified perceived readiness of the education system for digital transformation as the first differentiating characteristic. Among students who considered the education system ready, gender produced the next split: 42.2% of women and 58.9% of men were in Cluster 1, whereas 57.8% of women and 41.1% of men were in Cluster 2. Among students who considered the education system not ready, self-rated knowledge of digital transformation produced the next split: 68.5% of students with knowledge scores of 5 or lower were in Cluster 1 compared with 53.3% of those with scores above 5 ((Fig. 3).

Discussion

The psychometric findings support the internal structure and internal consistency of the 19-item EDTRS. The KMO result, significant Bartlett test, 66.4% explained variance, factor loadings, reliability coefficients, and CFA results

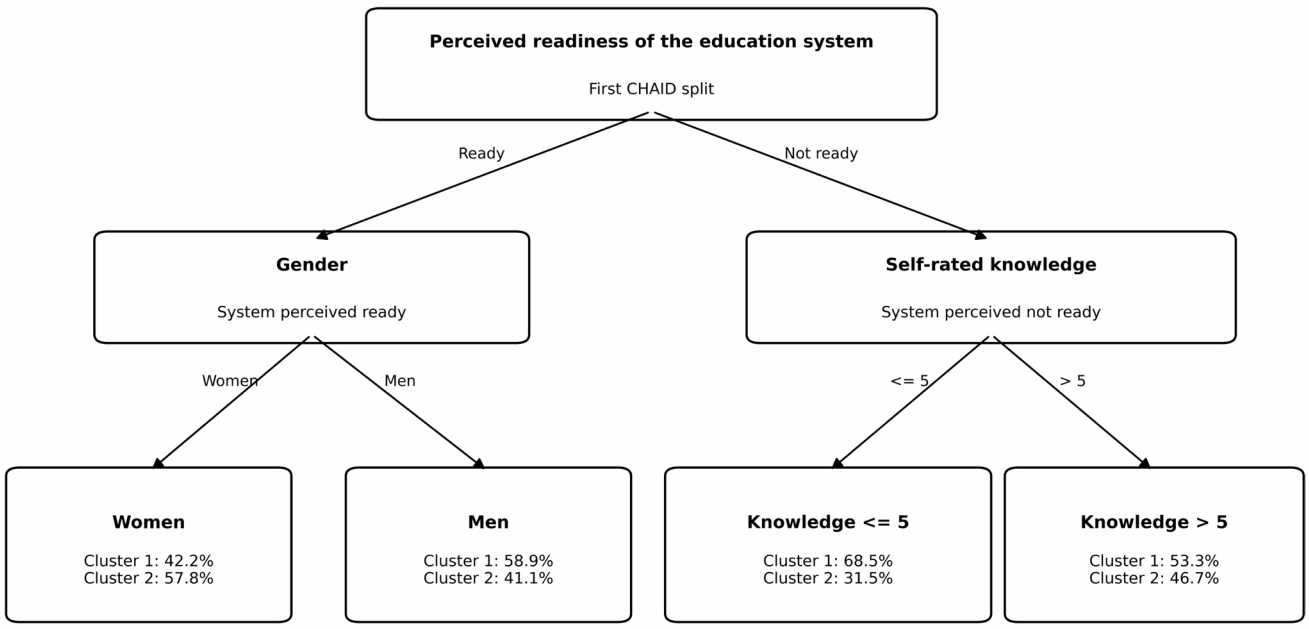

Fig. 3 Exploratory CHAID decision-tree summary with cluster membership as the dependent variable

collectively provide a coherent basis for interpreting the two-factor solution. These indices are reported as psychometric evidence rather than discussed as textbook thresholds, allowing the discussion to focus on what the resulting construct and profiling findings mean for higher education.

The most important conceptual result is that the final scale did not yield separate knowledge, skill, and attitude dimensions. Although the initial rationale framed readiness broadly in those terms, the development documentation did not record predetermined item-level assignments to three mutually exclusive subscales. The empirical covariance structure of the retained items was instead organized around Behavioral Attitude and Affective Attitude. The use of 'Affective Attitude' is a terminological refinement of the original English label 'Emotional Attitude' and reflects established affective-behavioral language in attitude research; it does not alter the item allocation or factor solution (Breckler, 1984). Accordingly, the final EDTRS should not be presented as a comprehensive measure of digital competence. Competence-focused instruments assess what students know or can do with digital technologies and may include content management, creation, communication, safety, and related capabilities (Mejías-Acosta et al., 2024), whereas the EDTRS captures students' attitudinal orientation toward engaging with digital transformation.

This narrower interpretation also clarifies the relation of the EDTRS to self-efficacy and learner autonomy. Confidence in one's capability to use a specific technology is a distinct construct, as illustrated by the GSE-6AI for AI-related self-efficacy (Morales-García et al., 2024). Likewise, self-regulated and self-directed learning involve forethought, planning, monitoring, motivation, and reflective control that can shape whether students engage effectively in technology-enabled learning (Achuthan, 2025). The EDTRS therefore represents one psychologically meaningful component of readiness, not its entirety. Future readiness assessments may be strongest when attitudinal scores are combined with objective competence measures, technology-related self-efficacy, and indicators of self-regulation.

The secondary data-mining phase was designed to extend interpretation after validation, not to validate the scale a second time. Cluster analysis showed that students were not homogeneous: two profiles emerged with relatively lower and higher scores across both Behavioral and Affective Attitude. This person-centered perspective is educationally useful because a single mean score can obscure groups that may require different forms of support. Students who are behaviorally hesitant to engage with digital change may need opportunities for guided practice and trial, whereas students with less favorable affective orientations may benefit from clearer expectations, supportive learning experiences, and opportunities to reduce uncertainty about new technologies.

Perceived readiness of the education system emerged as the first CHAID split, suggesting that student attitudes are embedded in perceptions of the broader environment. This result should not be interpreted causally, but it is compatible with contemporary models in which digital readiness involves both individual preparedness and institutional capacity. Chounta et al. (2024) argue that higher education digital readiness should incorporate organizational and data-informed indicators rather than relying only on individual self-reports. Similarly, the European Commission's Digital Education Action Plan emphasizes a high-performing digital education ecosystem that combines infrastructure and connectivity with organizational capability, digitally competent educators, accessible tools, and digital skills (European Commission, 2020). In Türkiye, the Twelfth Development Plan (2024–2028) also emphasizes digital transformation, emerging technologies, and institutional capacity. (Presidency of the Republic of Türkiye, 2023). The present findings therefore support viewing student readiness as situated within a visible and credible institutional transformation process rather than as an individual responsibility alone.

Adoption and diffusion dynamics offer an additional explanation for this system-level pattern. Educational innovations become normalized not simply because they are available but because learners can see their relevance, try them in meaningful contexts, engage with them repeatedly, and encounter supportive social and organizational structures. Evidence from virtual-laboratory diffusion in higher education highlights the importance of trialability, relative advantage, relevance, and engagement in adoption processes (Achuthan et al., 2020). From this perspective, institutions may strengthen Behavioral and Affective Attitude by embedding digital practices consistently across courses, making the purpose of new technologies explicit, providing low-risk opportunities for experimentation, and ensuring that students experience transformation as coherent rather than fragmented.

Gender appeared as a differentiating characteristic only among students who perceived the education system as ready. This conditional pattern is more informative than a simple overall gender comparison because it indicates that gender operated within a particular contextual branch. Recent work has identified gender and field-related variation in technology readiness while also warning that such variation can contribute to digital inequity (Heilala et al., 2026). The split should therefore not be read as an inherent difference between women and men. Prior exposure, confidence, disciplinary opportunities, accessibility, usability, and inclusion may all shape the conditions under which students engage with digital technologies. Inclusive digital transformation requires attention to these conditions and to the possibility that design choices can create unequal participation or reproduce bias (Kinnula et al., 2021).

Among students who perceived the education system as not ready, self-rated knowledge became the next differentiating characteristic, with lower knowledge more frequently associated with the relatively lower-readiness profile. This pattern suggests that conceptual understanding may become especially important when students have limited confidence in the surrounding system. It also reinforces the need to distinguish knowledge from attitude: self-rated knowledge differentiated profiles but did not emerge as a latent EDTRS factor. Interventions may therefore combine transparent institutional communication with opportunities to build digital knowledge, self-efficacy, and self-regulatory capacity through authentic learning tasks and supported practice (Achuthan, 2025; Bhutto et al., 2025; Morales-García et al., 2024).

The CHAID model should nevertheless be interpreted cautiously. Its error rate of.401 was lower than the majority-class baseline error of.437, but the improvement in accuracy was only 3.6 percentage points. Therefore, the value of the tree in this study is primarily interpretive: it provides a transparent hierarchy of characteristics associated with the empirically derived profiles. Psychometrics and data mining serve complementary purposes here. Psychometric analyses establish the structure and reliability of what is being measured; clustering and CHAID then explore how score patterns are distributed across students and contextual characteristics. The latter should not be treated as evidence of causation or as a high-performance predictive model without independent validation.

Limitations and future research

Several limitations should be considered. First, the study was conducted with fourth-year students from a single state university, which limits generalizability to other institutions, disciplines, educational levels, and national contexts. Second, the pilot sample of 25 was small relative to the 32-item draft instrument; pilot-stage internal-consistency coefficients should therefore be interpreted as preliminary item-screening evidence. Third, the EDTRS is a self-report instrument and captures attitudinal readiness rather than directly observed digital competence, self-regulatory behavior, or institutional readiness. Fourth, the available scale-development documentation did not record a formal a priori item-to-domain mapping for the broad knowledge/skill/attitude framing; consequently, changes in domain coverage after item deletion cannot be reconstructed without imposing a post hoc classification. Fifth, the Information Form predictors used for exploratory decision-tree profiling differed in measurement level and precision. Sixth, measurement invariance across demographic groups, test–retest reliability, and criterion-related validity were not examined. Finally, the decision-tree analysis was exploratory and was not independently validated in an external sample; the modest improvement over the majority-class baseline should not be generalized as predictive performance. Future studies should cross-validate the EDTRS in larger multisite and cross-cultural samples, test measurement invariance and temporal stability, compare EDTRS scores with objective digital-competence measures, self-efficacy, and self-regulation, and independently validate the stability of the cluster and decision-tree patterns.

Conclusion and recommendations

This study developed a 19-item EDTRS with two empirically supported subdimensions, Behavioral Attitude and Affective Attitude, and demonstrated strong internal-consistency and construct-validity evidence in the study sample. The final structure narrows the interpretation of the instrument: although the initial conceptual rationale referred broadly to knowledge, skills, and attitudes, the empirical factor solution did not support separate knowledge and skill dimensions. The EDTRS should therefore be used as a measure of students' attitudinal readiness for digital transformation in education rather than as a comprehensive test of digital competence.

The secondary cluster and CHAID analyses showed that attitudinal readiness was heterogeneous and context-sensitive. Perceived readiness of the education system was the primary differentiating characteristic, followed conditionally by gender and self-rated knowledge. These findings suggest that higher education institutions should combine student-level support with coherent institutional strategies, meaningful opportunities to engage with digital innovations, inclusive and accessible design, and transparent communication about digital transformation. For comprehensive readiness assessment, the EDTRS can be complemented by objective competence measures and indicators of self-efficacy, self-regulation, and institutional digital capacity. Replication in independent and diverse samples is required before the identified profiles are used for high-stakes decisions.

Acknowledgements The authors are grateful to the participated in this study.

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Author contributions EŞ, AK and NY contributed equally to the conception and design of the study and analyzed the data. Both authors drafted and revised the manuscript and read and approved the final version.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability The data of the research will be shared by the researchers with the requesting person(s) if requested.

Declarations

Ethics approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The, submitted article is methodological research in which data is collected from people
Ethics committee permission was obtained from the Istanbul Unıversıty-Cerrahpaşa Social and Human Sciences Research Ethics Committee in accordance with the [Date: 16.03.2023 Number: 642955].

Consent to publish The participants has consented to the submission of the research to the journal.
The authors affirm that human research participants provided informed consent for publication.

Conflicting interests The authors report there are no competing interests to declare.

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