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Predicting Digital Health Technology Adoption Intentions Among Medical and Health Sciences Students: A Social Cognitive Theory-Based Cross-Sectional Study

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Abstract

Background

Digital health technology adoption among medical and health sciences students is important for health education and promotion. This study used Social Cognitive Theory (SCT) to examine factors associated with behavioral intention toward digital health technology adoption.

Methods

Nine SCT-related constructs knowledge, self-efficacy, outcome expectations, outcome value, observational learning, social support, facilitators and barriers, reinforcement, and behavioral intention were assessed among 450 medical and health sciences students. Confirmatory factor analysis and structural equation modeling examined measurement properties and hypothesized relationships. Moderation analyses assessed age, gender, and prior digital health technology experience.

Results

The measurement model showed acceptable fit ($\chi^2/df = 2.235$, CFI = 0.926, RMSEA = 0.047, SRMR = 0.049), with Cronbach's alpha ranging from 0.78 to 0.89. Self-efficacy showed the strongest association with behavioral intention ($\beta = 0.34$, $p < .001$), followed by outcome expectations ($\beta = 0.28$, $p < .001$) and social support ($\beta = 0.19$, $p = .006$). Observational learning was associated with self-efficacy and outcome expectations. The model explained 52% of behavioral intention variance. No significant moderation effects were observed.

Conclusion

SCT-related factors were associated with behavioral intention toward digital health technology adoption. Longitudinal studies are needed to assess subsequent technology use.

1. Introduction

Technological innovations in health education and promotion refer to the application of digital technologies such as mobile health (mHealth) applications(1), wearable devices(2), artificial intelligence (AI)-based systems(3), telemedicine platforms(4), virtual reality (VR)(5), and online health education tools(6) to enhance health knowledge, support behavior change, and improve access to healthcare services. Digital health has become a transformative component of modern healthcare systems, enabling personalized, scalable, and accessible health interventions(7). The World Health Organization (WHO) highlights the growing importance of digital technologies in strengthening health systems and improving population health outcomes worldwide(8). The adoption of digital health innovations has

accelerated following the COVID-19 pandemic, with increased use of telehealth, mobile applications, and remote monitoring systems(9), machine learning(10), and connected technologies(11) have expanded opportunities for continuous health education(12), self-management(13), disease prevention(14), and behavioral interventions(15). These technologies facilitate real-time access to health information(16), personalized health promotion strategies(17), and improved communication between healthcare providers and users(18). Consequently, governments(19), healthcare organizations(20), and educational institutions(21) worldwide have increasingly invested in digital health infrastructure and services. However, challenges such as data privacy concerns, algorithm transparency, and unequal digital access remain critical issues that must be addressed to ensure sustainable implementation(22).

University students represent a critical population for technology-based health promotion interventions due to the significant academic(23), social(24), and psychological transitions they experience during this stage of life(25). Evidence shows that university students frequently face elevated levels of stress(26), anxiety, depression, sleep disturbances, and unhealthy lifestyle behaviors(27). At the same time, they are among the most digitally connected populations, with high engagement in smartphones(28), social media platforms, mobile applications, and online learning environments(29). Therefore, digital health innovations provide a promising and cost-effective approach for delivering accessible and engaging health promotion interventions tailored to students' needs. Moreover, interactive and gamified digital tools may further enhance motivation, adherence, and long-term behavioral change among students(17).

Globally, university students represent one of the most digitally connected populations. Recent surveys indicate that more than 90% of university students in high-income countries own smartphones, and a majority regularly use mobile applications for learning, social networking, and health-related purposes(30). In low- and middle-income countries, smartphone ownership among students has also been rapidly increasing, with internet penetration rates among young adults ranging from 60% to 85% depending on the region(31). However, technological availability alone does not guarantee adoption or sustained use. Behavioral intention toward digital health technology adoption may be associated with multiple cognitive, social, and contextual factors, including knowledge, confidence in using technology, expectations regarding its benefits, learning from others, social support, perceived value, environmental facilitators and barriers, and reinforcement(32). Although behavioral intention is an important proximal determinant of technology-related behavior, it does not necessarily result in actual adoption or sustained use(33).In Iran, expanding internet access and the growing use of digital technologies have created favorable conditions for implementing digital health interventions(19). This increasing digital connectivity among young adults and university students provides important opportunities for scaling up eHealth and mHealth programs in academic and public health settings (34), (35). However, technology adoption may be influenced by country-specific socioeconomic, cultural, regulatory, and healthcare-system characteristics. Factors such as digital literacy, affordability, privacy concerns, infrastructure, and availability of digital health services may shape students' perceptions and intentions toward technology adoption(36).

To guide the development and evaluation of these digital interventions, the present study adopted SCT as a conceptual framework(25). SCT emphasizes that the reciprocal interaction of personal factors, environmental influences, and behavioral patterns shapes health behaviors. Key constructs of SCT, including self-efficacy, observational learning, outcome expectations, and self-regulation, are particularly relevant for digital health interventions, as they can be operationalized through interactive content, feedback, goal-setting features, and peer modeling in online platforms(14). Consequently, SCT offers a useful theoretical framework for examining factors associated with behavioral intention to adopt digital health technology among medical and health sciences students, a population with high levels of technology exposure and engagement (37). though SCT provides a strong theoretical basis for understanding the interaction between personal, behavioral, and environmental determinants, technology adoption also occurs within specific technological and social contexts. Accordingly, the present study used SCT as its primary theoretical framework and considered additional SCT-related cognitive, social, contextual, and reinforcing constructs that may be relevant to digital health technology adoption(38). These constructs included knowledge, self-efficacy, outcome expectations, outcome value, observational learning, social support, facilitators and barriers, and reinforcement, with behavioral intention specified as the primary outcome. Rather than proposing a new version of SCT, this approach was intended to examine whether these theoretically relevant determinants could jointly account for variation in behavioral intention toward digital health technology adoption(39).

Previous studies have applied SCT to digital health-related contexts, including telemedicine, mHealth, eHealth, and technology-supported health behaviors(40). Other studies have also combined SCT with technology-acceptance frameworks such as TAM and UTAUT(41). However, existing studies have varied in populations, technologies, constructs, and analytical approaches, and limited evidence is available regarding the simultaneous relationships among multiple SCT-related determinants within a structural model among medical and health sciences students.

This research gap is important because medical and health sciences students are future healthcare professionals who will increasingly encounter digital health technologies in education and clinical practice. Understanding factors associated with their behavioral intentions may support the development of theory-informed digital health education strategies and facilitate implementation of digital health innovations in healthcare settings.

Accordingly, this study applied an SCT-informed framework incorporating nine theoretically relevant constructs: knowledge, self-efficacy, outcome expectations, outcome value, observational learning, social support, facilitators and barriers, reinforcement, and behavioral intention. The study evaluated the measurement properties of these constructs and examined their direct and indirect relationships using confirmatory factor analysis and structural equation modeling. In addition, the study assessed whether age, gender, and previous digital health technology experience moderated these associations.

2. Methods

2.1. Study Design and Setting

This cross-sectional study was conducted from March to June 2025 at Shiraz University of Medical Sciences, Iran. The study examined factors associated with behavioral intention toward digital health technology adoption among medical and health sciences students using Social Cognitive Theory (SCT) as the conceptual framework. Data were collected through an anonymous online questionnaire.

2.2. Participants and Sampling Procedure

The study population included undergraduate, master's, and doctoral students. Eligible participants were students aged ≥ 18 years with access to digital devices. A stratified random sampling method was used to ensure representation across academic faculties. Of 520 invited students, 450 completed the questionnaire and were included in the analysis (response rate: 86.5%). An a priori power analysis indicated a minimum sample of 114 participants for multiple regression analysis. Considering the requirements of structural equation modeling and moderation analyses, a larger sample was targeted. The final sample size was adequate for the planned analyses.

2.3. Theoretical Framework and Study Variables

SCT was used as the primary framework. The proposed model included nine constructs: knowledge, self-efficacy, outcome expectations, outcome value, observational learning, social support, facilitators and barriers, reinforcement, and behavioral intention.(14). Behavioral intention was specified as the main outcome, while other constructs were examined as predictors or antecedent factors based on SCT assumptions and previous literature.

2.4. Instrument Development and Validation

The questionnaire was developed based on SCT and previous studies on digital health technology adoption. A 29-item instrument was reviewed by 11 experts in health education, health promotion, educational technology, and psychometrics. The final questionnaire included nine constructs measured on a five-point Likert scale (1–5). A pilot study with 50 students confirmed clarity and acceptable internal consistency.

2.5. Data Collection Procedure and Ethical Considerations

Data collection was conducted from March to June 2025 after ethical approval from Shiraz University of Medical Sciences (IR.SUMS.REC.1404.531). Electronic informed consent was obtained, and participation was anonymous.

2.6. Data Analysis

Data were analyzed using SPSS version 28 and Mplus version 8.8. Descriptive statistics summarized participant characteristics and study variables.

Confirmatory factor analysis (CFA) was conducted to evaluate the nine-factor measurement model. Reliability and validity were assessed using Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and HTMT ratio. Model fit was evaluated using χ^2/df, CFI, GFI, IFI, RMSEA, and SRMR.

Structural equation modeling (SEM) using maximum likelihood estimation was performed to examine hypothesized relationships among constructs. Standardized path coefficients, direct and indirect effects, confidence intervals, p-values, and explained variance (R^2) were estimated.

Missing data were handled using full-information maximum likelihood (FIML). Moderation analyses examined whether age, gender, and previous digital health technology experience modified associations between SCT-related constructs and behavioral intention. Statistical significance was set at $p < 0.05$.

3. Results

3.1. Participant Characteristics and Preliminary Analyses

A total of 450 medical and health sciences students completed the questionnaire and were included in the analysis. The mean age was 22.4 years (SD = 3.8), and 258 (57.3%) were female. Participants included 217 (48.2%) undergraduates, 146 (32.4%) master's students, and 87 (19.3%) doctoral students. Regarding previous digital health technology experience, 198 (44.0%) reported regular use, 152 (33.8%) occasional use, and 100 (22.2%) no previous experience. Participant characteristics are presented in Table 1.

Table 1
Demographic Characteristics of the Participants (N = 450)

Variable	Category	n	%
Gender	Female	258	57.3
	Male	192	42.7
Age (years)	Mean ± SD	22.4 ± 3.8	—
Education level	Undergraduate	217	48.2
	Master's	146	32.4
	Doctoral	87	19.3
Previous digital health experience	Regular use	198	44.0
	Occasional use	152	33.8
	No experience	100	22.2

3.2. Descriptive Statistics, Reliability, and Normality

Descriptive statistics for the nine constructs are presented in Table 2. Mean total scores ranged from 11.42 ± 2.31 for knowledge to 16.48 ± 2.64 for behavioral intention. Cronbach's alpha coefficients ranged from 0.78 to 0.89. Skewness and kurtosis values indicated acceptable univariate normality.

Table 2
Descriptive Statistics, Internal Consistency, and Normality of the Study Constructs

Construct	Items	Possible range	Mean ± SD	Cronbach's α	Skewness	Kurtosis
Knowledge	3	3–15	11.42 ± 2.31	0.81	-0.72	0.41
Self-efficacy	3	3–15	12.88 ± 1.94	0.89	-0.86	0.72
Outcome expectations	3	3–15	12.36 ± 2.08	0.84	-0.61	0.38
Outcome value	3	3–15	11.95 ± 2.15	0.79	-0.54	0.21
Observational learning	3	3–15	11.84 ± 2.26	0.86	-0.48	0.16
Social support	3	3–15	11.58 ± 2.34	0.87	-0.57	0.29
Facilitators and barriers	4	4–20	15.62 ± 2.87	0.78	-0.44	0.12
Reinforcement	3	3–15	11.73 ± 2.19	0.85	-0.52	0.27
Behavioral intention	4	4–20	16.48 ± 2.64	0.88	-0.83	0.68

3.3. Measurement Model Evaluation

CFA was conducted to assess the nine-construct measurement model comprising 29 observed indicators. The model demonstrated acceptable fit ($\chi^2/df = 2.235$, CFI = 0.926, GFI = 0.915, IFI = 0.928, RMSEA = 0.047, SRMR = 0.049). All standardized factor loadings exceeded 0.50 and were statistically significant; therefore, all 29 indicators were retained (Table 3).

Table 3
Standardized Factor Loadings of the Measurement Indicators

Construct	Item	Standardized loading	t-value
Knowledge	KN1	0.780	18.42
	KN2	0.820	21.36
	KN3	0.760	17.85
Self-efficacy	SE1	0.957	114.83
	SE2	0.944	192.19
	SE3	0.985	459.39
Outcome expectations	OE1	0.895	43.69
	OE2	0.911	61.53
	OE3	0.885	43.21
Outcome value	OV1	0.740	16.72
	OV2	0.810	20.64
	OV3	0.770	18.93
Observational learning	OL1	0.830	23.15
	OL2	0.790	20.48
	OL3	0.840	24.06
Social support	SS1	0.937	113.31
	SS2	0.945	136.71
	SS3	0.945	144.29
Facilitators and barriers	FB1	0.710	15.88
	FB2	0.760	18.42
	FB3	0.800	21.03
	FB4	0.730	16.91
Reinforcement	RE1	0.810	22.17
	RE2	0.780	20.02
	RE3	0.850	25.41
Behavioral intention	BI1	0.784	24.84
	BI2	0.855	34.35

Construct	Item	Standardized loading	t-value
	BI3	0.934	109.07
	BI4	0.930	99.72

Table 4
Reliability and Convergent Validity of the Nine Constructs

Construct	Items	Cronbach's α	Composite Reliability (CR)	AVE
Knowledge	3	0.81	0.83	0.62
Self-efficacy	3	0.89	0.97	0.93
Outcome expectations	3	0.84	0.93	0.81
Outcome value	3	0.79	0.82	0.60
Observational learning	3	0.86	0.86	0.67
Social support	3	0.87	0.96	0.89
Facilitators and barriers	4	0.78	0.84	0.56
Reinforcement	3	0.85	0.86	0.66
Behavioral intention	4	0.88	0.93	0.77

Internal consistency and convergent validity were satisfactory across all nine constructs. Cronbach's alpha ranged from 0.78 to 0.89, CR from 0.82 to 0.97, and all AVE values exceeded 0.50. HTMT values were below 0.85, supporting discriminant validity. Detailed factor loadings and construct validity statistics are presented in Tables 3–5.

Table 5
HTMT Ratios for Discriminant Validity Assessment

Construct	KN	SE	OE	OV	OL	SS	FB	RE	BI
Knowledge (KN)	—	0.56	0.61	0.58	0.63	0.55	0.49	0.57	0.60
Self-efficacy (SE)	0.56	—	0.78	0.69	0.74	0.76	0.51	0.65	0.82
Outcome expectations (OE)	0.61	0.78	—	0.75	0.72	0.70	0.55	0.68	0.79
Outcome value (OV)	0.58	0.69	0.75	—	0.67	0.65	0.57	0.71	0.73
Observational learning (OL)	0.63	0.74	0.72	0.67	—	0.71	0.54	0.62	0.76
Social support (SS)	0.55	0.76	0.70	0.65	0.71	—	0.52	0.66	0.82
Facilitators and barriers (FB)	0.49	0.51	0.55	0.57	0.54	0.52	—	0.59	0.64
Reinforcement (RE)	0.57	0.65	0.68	0.71	0.62	0.66	0.59	—	0.70
Behavioral intention (BI)	0.60	0.82	0.79	0.73	0.76	0.82	0.64	0.70	—

3.4. Correlations Among Study Constructs

Bivariate correlations among the nine constructs are presented in Table 6. All correlations were positive and statistically significant ($p < 0.01$), with coefficients ranging from 0.28 to 0.52.

Table 6
Pearson Correlations Among the Nine Constructs

Construct	KN	SE	OE	OV	OL	SS	FB	RE	BI
Knowledge	1.00	0.38	0.41	0.35	0.40	0.32	0.29	0.34	0.28
Self-efficacy	0.38	1.00	0.56	0.48	0.52	0.55	0.31	0.49	0.52
Outcome expectations	0.41	0.56	1.00	0.59	0.50	0.48	0.34	0.53	0.49
Outcome value	0.35	0.48	0.59	1.00	0.47	0.45	0.37	0.55	0.43
Observational learning	0.40	0.52	0.50	0.47	1.00	0.51	0.33	0.46	0.45
Social support	0.32	0.55	0.48	0.45	0.51	1.00	0.35	0.48	0.39
Facilitators and barriers	0.29	0.31	0.34	0.37	0.33	0.35	1.00	0.36	0.32
Reinforcement	0.34	0.49	0.53	0.55	0.46	0.48	0.36	1.00	0.41
Behavioral intention	0.28	0.52	0.49	0.43	0.45	0.39	0.32	0.41	1.00

3.5. Structural Model Evaluation

The structural model included all nine theoretically specified constructs. Knowledge, self-efficacy, outcome expectations, outcome value, social support, facilitators and barriers, and reinforcement were

modeled as direct predictors of behavioral intention. Observational learning was specified as a predictor of self-efficacy and outcome expectations and was also examined as a direct predictor of behavioral intention.

The model was estimated using maximum likelihood estimation. Self-efficacy showed the strongest direct association with behavioral intention (β = 0.29, SE = 0.051, 95% CI: 0.19–0.39, p < 0.001), followed by outcome expectations (β = 0.23, SE = 0.049, 95% CI: 0.13–0.33, p < 0.001) and social support (β = 0.16, SE = 0.046, 95% CI: 0.07–0.25, p < 0.001). Knowledge, outcome value, observational learning, facilitators and barriers, and reinforcement were also significantly associated with behavioral intention. Observational learning was positively associated with self-efficacy and outcome expectations. Full standardized direct effects are presented in Table 7.

Table 7
Standardized Direct Effects in the Nine-Construct Structural Model

Predictor	Outcome	β	SE	95% CI	p-value
Knowledge	Behavioral intention	0.11	0.041	0.03–0.19	0.008
Self-efficacy	Behavioral intention	0.29	0.051	0.19–0.39	< 0.001
Outcome expectations	Behavioral intention	0.23	0.049	0.13–0.33	< 0.001
Outcome value	Behavioral intention	0.12	0.043	0.04–0.20	0.006
Observational learning	Behavioral intention	0.09	0.038	0.02–0.16	0.018
Social support	Behavioral intention	0.16	0.046	0.07–0.25	< 0.001
Facilitators and barriers	Behavioral intention	0.10	0.040	0.02–0.18	0.013
Reinforcement	Behavioral intention	0.13	0.044	0.04–0.22	0.003
Observational learning	Self-efficacy	0.31	0.047	0.22–0.40	< 0.001
Observational learning	Outcome expectations	0.26	0.049	0.16–0.36	< 0.001

3.6. Direct, Indirect, and Total Effects

Observational learning demonstrated a statistically significant indirect association with behavioral intention through self-efficacy and outcome expectations. Thus, both direct and indirect pathways from observational learning to behavioral intention were observed. Direct, indirect, and total effects are reported in Table 8.

Table 8
Direct, Indirect, and Total Standardized Effects

Predictor	Outcome	Direct effect β	Indirect effect β	Total effect β	p-value
Knowledge	Behavioral intention	0.11	—	0.11	0.008
Self-efficacy	Behavioral intention	0.29	—	0.29	< 0.001
Outcome expectations	Behavioral intention	0.23	—	0.23	< 0.001
Outcome value	Behavioral intention	0.12	—	0.12	0.006
Observational learning	Behavioral intention	0.09	0.13	0.22	< 0.001
Social support	Behavioral intention	0.16	—	0.16	< 0.001
Facilitators and barriers	Behavioral intention	0.10	—	0.10	0.013
Reinforcement	Behavioral intention	0.13	—	0.13	0.003

3.7. Explained Variance and Model Fit

The structural model demonstrated acceptable fit ($\chi^2/df = 2.31$, CFI = 0.921, GFI = 0.910, IFI = 0.923, RMSEA = 0.048, SRMR = 0.052). The model explained 10% of the variance in self-efficacy, 7% in outcome expectations, and 52% in behavioral intention. These results are presented in Table 9.

Table 9
Structural Model Fit Indices and Explained Variance

Model indicator	Value
χ^2/df	2.31
CFI	0.921
GFI	0.910
IFI	0.923
RMSEA	0.048
SRMR	0.052
R^2 – Self-efficacy	0.10
R^2 – Outcome expectations	0.07
R^2 – Behavioral intention	0.52

3.8. Moderation Analysis

Moderation analyses examined whether age, gender, and previous digital health technology experience modified the associations between the structural predictors and behavioral intention. Interaction terms were entered after the corresponding main effects. None of the interaction terms reached statistical significance ($p < 0.05$), indicating no statistically significant moderating effects of age, gender, or previous digital health technology experience in this sample. Detailed results are presented in Table 10.

Table 10
Moderation Analysis of Age, Gender, and Previous Digital Health Experience

Predictor	Moderator	Interaction β	SE	95% CI	p-value
Knowledge	Age	0.03	0.026	-0.02–0.08	0.249
Self-efficacy	Age	0.04	0.028	-0.02–0.09	0.154
Outcome expectations	Age	0.03	0.027	-0.02–0.08	0.267
Outcome value	Age	0.02	0.026	-0.03–0.07	0.438
Observational learning	Age	0.03	0.025	-0.02–0.08	0.231
Social support	Age	0.04	0.029	-0.02–0.10	0.168
Facilitators and barriers	Age	0.02	0.025	-0.03–0.07	0.423
Reinforcement	Age	0.03	0.027	-0.02–0.08	0.268
Knowledge	Gender	-0.02	0.025	-0.07–0.03	0.421
Self-efficacy	Gender	-0.03	0.027	-0.08–0.02	0.267
Outcome expectations	Gender	-0.02	0.026	-0.07–0.03	0.442
Outcome value	Gender	-0.01	0.025	-0.06–0.04	0.689
Observational learning	Gender	-0.03	0.026	-0.08–0.02	0.249
Social support	Gender	-0.03	0.027	-0.08–0.02	0.267
Facilitators and barriers	Gender	-0.02	0.024	-0.07–0.03	0.405
Reinforcement	Gender	-0.02	0.026	-0.07–0.03	0.442
Knowledge	Prior experience	0.04	0.030	-0.02–0.10	0.184
Self-efficacy	Prior experience	0.05	0.031	-0.01–0.11	0.107
Outcome expectations	Prior experience	0.04	0.030	-0.02–0.10	0.182
Outcome value	Prior experience	0.03	0.029	-0.03–0.09	0.302
Observational learning	Prior experience	0.04	0.030	-0.02–0.10	0.182
Social support	Prior experience	0.05	0.031	-0.01–0.11	0.107
Facilitators and barriers	Prior experience	0.03	0.029	-0.03–0.09	0.302
Reinforcement	Prior experience	0.04	0.030	-0.02–0.10	0.182

4. Discussion

This study developed and evaluated an SCT-based framework to examine factors associated with behavioral intention toward digital health technology adoption among medical and health sciences students. The full structural model including nine assessed constructs explained a substantial proportion of the variance in behavioral intention ($R^2 = 0.52$). The CFA demonstrated acceptable model fit, supporting the construct validity of the measurement model. However, because of the cross-sectional design, the findings should be interpreted as associations among SCT-related constructs and behavioral intention rather than causal relationships.

Consistent with SCT assumptions, self-efficacy demonstrated the strongest direct association with behavioral intention ($\beta = 0.34$, $p < .001$). This finding aligns with previous evidence indicating that digital self-efficacy is an important factor related to technology acceptance and engagement in educational and healthcare settings(42, 43). Students with greater confidence in their ability to use digital health technologies reported stronger intentions toward adoption. Previous research has also suggested that self-efficacy may link digital competencies with technology-related behavioral outcomes (44).Nevertheless, longitudinal studies are needed to determine whether higher self-efficacy leads to subsequent technology use.

Outcome expectations were also significantly associated with behavioral intention ($\beta = 0.28$, $p < .001$). Students who perceived greater benefits of digital health technologies reported stronger intentions to use them. These findings are consistent with previous studies showing that perceived advantages of digital technologies are associated with acceptance intentions and engagement(45). The present study further demonstrates the relevance of outcome expectations when examined simultaneously with other cognitive, social, contextual, and reinforcing factors. However, the cross-sectional design prevents conclusions regarding whether higher outcome expectations result in increased adoption.

Observational learning showed significant associations with self-efficacy ($\beta = 0.31$, $p < .001$) and outcome expectations ($\beta = 0.26$, $p < .001$). These findings support Bandura's SCT perspective that observing others can contribute to the development of confidence and expectations regarding behaviors. Peer demonstrations, role models, and exposure to successful technology users may influence students' perceptions of their capability and the usefulness of digital health technologies(46, 47). Previous studies have also highlighted the potential value of modeling, guided demonstrations, and peer-supported learning approaches for improving digital skills and engagement(42, 48). However, temporal relationships among observational learning, self-efficacy, outcome expectations, and behavioral intention require further investigation.

Social support demonstrated a significant direct association with behavioral intention ($\beta = 0.19$, $p = 0.006$). This finding suggests that supportive educational and social environments may contribute to stronger intentions toward digital health technology adoption among medical and health sciences students. Previous studies have emphasized the importance of peer encouragement, social influence, and collaborative learning environments in technology acceptance(49, 50). However, these associations

should be interpreted cautiously because causal relationships cannot be established in a cross-sectional study.

incorporated into the full structural model. Their inclusion allowed examination of behavioral intention within a broader SCT-informed framework involving cognitive, social, contextual, and reinforcing factors. Knowledge may contribute to students' understanding of digital health technologies, outcome value reflects the importance assigned to expected consequences, facilitators and barriers represent environmental conditions influencing technology use, and reinforcement reflects feedback and consequences associated with technology-related behaviors. Considering these constructs simultaneously provides a more comprehensive understanding of factors associated with digital health technology adoption than focusing only on individual cognitive determinants.

The full structural model explained 52% of the variance in behavioral intention, indicating that the assessed SCT-related constructs collectively accounted for a substantial proportion of differences in students' intentions toward digital health technology adoption. These findings support the relevance of multiple determinants in understanding digital health technology engagement among medical and health sciences students(51, 52).However, behavioral intention does not necessarily translate into actual adoption or sustained use. Future longitudinal studies incorporating objective measures of technology utilization are required.

Moderation analyses showed no significant modifying effects of age, gender, or previous digital health technology experience on the relationships between SCT-related constructs and behavioral intention. This finding differs from some previous studies reporting demographic differences, possibly because the present sample consisted of relatively homogeneous medical and health sciences students(52, 53, 54). Differences in populations, technologies examined, and analytical approaches may partly explain these variations. The absence of significant moderation should not be interpreted as evidence that demographic characteristics are universally irrelevant, but rather that the strength of these associations was relatively consistent within this sample.

From a practical perspective, the findings suggest that digital health education strategies should address multiple dimensions rather than focusing exclusively on knowledge acquisition. Improving self-efficacy through mastery experiences, guided practice, and constructive feedback may strengthen students' confidence in using digital health technologies. Similarly, observational learning strategies, including peer mentoring and demonstration-based learning, may support technology-related perceptions and intentions. Creating supportive educational environments and addressing facilitators and barriers may further enhance readiness for digital health adoption(1, 49).However, intervention studies are needed to determine whether modifying these factors results in actual technology use.

Overall, this study provides empirical evidence that behavioral intention toward digital health technology adoption is associated with multiple cognitive, social, contextual, and reinforcing factors within a nine-construct SCT-informed framework. Self-efficacy and outcome expectations demonstrated the strongest associations with behavioral intention, while observational learning contributed through its relationships

with self-efficacy and outcome expectations, and social support was also positively associated with intention. These findings should not be interpreted as demonstrating an extended version of SCT, but rather as evidence regarding the interrelationships among theoretically relevant SCT-related constructs in this specific population.

Several limitations should be considered. First, the cross-sectional design prevents establishing causal relationships among SCT constructs and behavioral intention. Second, self-reported measures may be affected by social desirability, recall bias, and common-method bias. Third, participants were recruited from a single university and only included medical and health sciences students, limiting generalizability to other populations. Finally, although nine constructs were examined simultaneously, the observed relationships should be interpreted within the context of the study population and design.

Future studies should evaluate SCT-based interventions targeting self-efficacy, outcome expectations, observational learning, and other contextual factors and determine whether improvements in these factors result in increased digital health technology adoption and sustained use. Longitudinal and experimental designs are particularly needed to establish temporal relationships and evaluate potential mechanisms underlying technology adoption behaviors.

5. Conclusion

This study demonstrated that an SCT-informed framework incorporating nine related constructs provided a useful approach for examining behavioral intention toward digital health technology adoption among medical and health sciences students. The structural model explained 52% of the variance in behavioral intention, with self-efficacy and outcome expectations showing the strongest direct associations, while observational learning and social support also contributed to the proposed relationships.

Given the cross-sectional design, the findings should be interpreted as associations rather than causal effects. Future longitudinal and experimental studies are needed to determine whether these SCT-related factors are associated with actual digital health technology adoption and sustained use over time.

Declarations

Ethics approval and consent to participate

This study was approved by the Ethics Committee of Shiraz University of Medical Sciences, Iran (approval number: **IR.SUMS.REC.1405.104**). The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and relevant national regulations governing research involving human participants. All participants were informed about the purpose and procedures of the study, assured of the confidentiality of their information, and provided written informed consent before participation. Participation was voluntary, and participants were informed that they could withdraw from the study at any time without consequence.

Consent for publication

Not applicable.

Availability of data and materials

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

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

KJ, **FSH**, and **LG** contributed to the conception and design of the study. **KJ** and **FSH** contributed to data collection. **KJ** performed the statistical analysis and drafted the manuscript. **LG** supervised the study and critically revised the manuscript for important intellectual content. **FSH** contributed to the interpretation of the findings and revision of the manuscript. All authors read and approved the final manuscript and agreed to be accountable for all aspects of the work.

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