

The Impact of E-Health Literacy on Perceived Access to Healthcare Services: A Cross-Sectional Study Among Health Sciences Students in Istanbul, Turkey

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Abstract

Background

The rapid digitalization of healthcare delivery has elevated e-health literacy to a critical competency for navigating modern health systems. Despite growing scholarly attention, evidence linking e-health literacy to perceived healthcare access among health sciences students – who represent the future healthcare workforce – remains limited, particularly in the Turkish context. This study examined the structural effect of e-health literacy on perceived access to healthcare services among health sciences students in Istanbul.

Methods

A quantitative cross-sectional study was conducted with 500 health sciences students from six universities in Istanbul, Turkey (ethics approval: Meeting No: 2026/02; Decision Date: 06 February 2026). The eHealth Literacy Scale (eHEALS) and a 23-item Perceived Access to Healthcare Services Scale (four dimensions: Accessibility, Acceptability, Accommodation, Affordability) were administered via structured questionnaire. Common method bias was assessed using Harman's single-factor test. Confirmatory Factor Analysis (CFA) and second-order Structural Equation Modeling (SEM) were performed in LISREL 9.3. Discriminant validity was evaluated through both the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratios.

Results

Harman's single-factor test yielded a largest component of 15.72% of total variance, well below the 25% common method bias threshold. The structural model demonstrated good fit ($\chi^2/df = 1.97$; RMSEA = 0.051; CFI = 0.96; TLI = 0.95; SRMR = 0.047). E-health literacy exerted a significant positive effect on perceived healthcare access ($\beta = 0.62$, $p < 0.001$, $R^2 = 0.38$). The Acceptability ($\lambda = 0.92$) and Accommodation ($\lambda = 0.90$) dimensions contributed most strongly to the higher-order access construct. All HTMT ratios fell below 0.60, confirming discriminant validity.

Conclusions

Higher e-health literacy is positively associated with more favorable perceptions of healthcare access among health sciences students. Integrating structured digital health competency training into health sciences curricula may strengthen future professionals' engagement with health systems and reduce digital health inequities. Longitudinal and cross-cultural replication studies are warranted.

Background

The digitalization of healthcare delivery has changed how individuals seek, evaluate, and act on health information. By early 2024, approximately 5.35 billion people — 66% of the global population — had internet access [1], transforming patterns of health information-seeking behavior and reshaping expectations of healthcare services. In this environment, e-health literacy — defined by Norman and Skinner as the ability to seek, find, understand, and critically evaluate electronic health information and apply it to health decisions [2] — has emerged as a consequential competency for both patients and future healthcare professionals [3].

Healthcare access itself is a multidimensional construct. Penchansky and Thomas proposed the foundational framework defining access as the "degree of fit" between patients' needs and the healthcare system's capacity to meet them, encompassing five dimensions: Availability, Accessibility, Accommodation, Affordability, and Acceptability [4]. Perceived access — the subjective evaluation of these dimensions — has been consistently linked to healthcare utilization, treatment adherence, and health outcomes [5, 6]. Recent extensions of the access model acknowledge digital competencies as a sixth determinant: Rowe and colleagues proposed "TechQuity," recognizing that individuals lacking e-health literacy face access barriers qualitatively distinct from those arising from geography or cost [5].

Health sciences students occupy a distinctive position in this context. As future healthcare professionals, they simultaneously function as digital health consumers and nascent practitioners whose perceptions of healthcare systems will shape both their personal health behavior and their professional practice. Despite near-universal internet access among young adults in Turkey, studies conducted in Turkish settings have documented substantial variability in e-health literacy competencies across health sciences students [7, 8, 9]. A systematic review by Rashid and colleagues, published in BMC Health Services Research, confirmed that digital health literacy is positively associated with healthcare access across diverse populations [10]. However, few studies have rigorously tested this relationship using structural equation modeling (SEM) with explicit controls for common method bias and discriminant validity confirmation through modern criteria such as the Heterotrait–Monotrait (HTMT) ratio [11].

The present study addresses these methodological gaps by: (1) evaluating psychometric properties via both Fornell–Larcker and HTMT criteria; (2) testing common method bias through Harman's single-factor procedure; and (3) examining the structural effect of e-health literacy on a second-order perceived healthcare access construct among 500 health sciences students in Istanbul, Turkey. The following hypothesis is tested:

H1: E-health literacy positively and significantly affects perceived access to healthcare services among health sciences students.

Methods

Study design, setting, and ethics

Ethics statement. This study was conducted in accordance with the Declaration of Helsinki and approved by the Social and Human Sciences Ethics Committee of Istanbul Kent University (Meeting No: 2026/02; Approval Date: 06 February 2026). All participants provided written informed consent before participation. No personal identifying information was collected or retained.

A quantitative cross-sectional design was used, which is appropriate for theory-testing when experimental manipulation is not feasible [12]. Data were collected between April and June 2026 from health sciences students enrolled at universities in Istanbul, Turkey.

Participants and sampling

The target population comprised all students enrolled in associate, undergraduate, and graduate health sciences programs in Istanbul. Convenience sampling was employed – a widely accepted approach in student-based theory-testing research [13, 14]. Survey forms were distributed both online (via institutional email) and face-to-face across multiple health sciences departments. After data screening (removal of incomplete responses and multivariate outlier detection via Mahalanobis distance; $p < 0.001$), 500 valid questionnaires were retained. This sample size substantially exceeds the minimum recommended for covariance-based SEM with large measurement models [13, 15].

Measurement instruments

E-Health Literacy Scale (eHEALS)

E-health literacy was measured using the eHEALS, developed by Norman and Skinner [3]. The scale consists of eight items assessing perceived confidence in finding, evaluating, and applying online health information (five-point Likert scale, 1 = Strongly Disagree to 5 = Strongly Agree). The Turkish version was used, validated in prior Turkish research [7, 8, 9]. The eHEALS has demonstrated strong psychometric properties across diverse populations including health sciences students and healthcare providers [16, 17, 18].

Perceived Access to Healthcare Services Scale

Perceived access was assessed using a 23-item scale organized into four dimensions aligned with the Penchansky and Thomas framework [4]: Accessibility (SHE1–SHE4; 4 items), Acceptability (SHE5–SHE12; 8 items), Accommodation (SHE13–SHE20; 8 items), and Affordability (SHE21–SHE23; 3 items). All items are scored on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Statistical analysis

Analysis proceeded in four sequential stages. First, normality was assessed through skewness ($|\text{threshold}| < 3$) and kurtosis ($|\text{threshold}| < 10$) following Kline [15] and Hair and colleagues [13]. Second, Harman's single-factor test was conducted in SPSS 26 as a control for common method bias (CMB): all 31 items were entered into an unrotated principal component analysis and the variance explained by the largest factor was compared against the 25% threshold [19]. Third, CFA was performed in LISREL 9.3 to evaluate the measurement model. Model fit was assessed via χ^2/df , RMSEA, CFI, TLI, and SRMR [20]. Construct reliability was assessed via Composite Reliability ($\text{CR} > 0.70$) and Cronbach's alpha. Convergent validity was assessed via Average Variance Extracted ($\text{AVE} > 0.50$) [21]. Discriminant validity was evaluated using two complementary criteria: the Fornell–Larcker criterion ($\sqrt{\text{AVE}}$ exceeds inter-construct correlations) [21] and the HTMT ratio (threshold < 0.85) [11]. Fourth, second-order SEM tested the hypothesized structural path from e-health literacy to the higher-order perceived access construct using maximum likelihood estimation [14, 15].

Results

Participant characteristics

Table 1 presents the demographic profile of the 500 participants. The sample was predominantly young, female (79.2%), and Turkish citizens (80.8%). International students constituted 19.2% of the sample. Nursing students formed the largest departmental subgroup (29.6%), followed by Child Development (16.4%) and Physiotherapy and Rehabilitation (12.6%). Almost half of participants were first-year students (47.6%), and 58.2% reported a middle-income background. Social media membership was near-universal (92.4%), and 83.2% had conducted health-related internet searches in the preceding week — a finding consistent with high digital engagement documented among Turkish health sciences students [7, 9].

Table 1
Demographic characteristics of the study sample (N = 500)

Variable	Category	n	%
Age	17–18	51	10.2
	19–21	261	52.2
	22–23	130	26.0
	24+	58	11.6
Gender	Female	396	79.2
	Male	104	20.8
Nationality	Turkish citizen	404	80.8
	International student	96	19.2
Department	Nursing	148	29.6
	Child Development	82	16.4
	Physiotherapy & Rehabilitation	63	12.6
	Nutrition & Dietetics	54	10.8
	Speech & Language Therapy	48	9.6
	Health Management	45	9.0
	Midwifery	34	6.8
	Pharmacy	26	5.2
Grade level	1st year	238	47.6
	2nd year	111	22.2
	3rd year	123	24.6
	4th year	28	5.6
Income level	Low	78	15.6
	Middle	291	58.2
	Good/Very Good	131	26.2
Social media membership	Yes	462	92.4
	No	38	7.6
Daily internet use	1–2 hours	48	9.6
	3–4 hours	232	46.4

Variable	Category	n	%
	5–6 hours	156	31.2
	7 + hours	64	12.8
Health internet search (last week)	Yes	416	83.2
	No	84	16.8

Age and income categories are grouped for presentational parsimony.

Normality and common method bias

Skewness and kurtosis values for all 31 items fell within acceptable thresholds ($|\text{skewness}| < 3$; $|\text{kurtosis}| < 10$) [13, 15]. Harman's single-factor test (Table 2) revealed that the largest single component explained only 15.72% of total variance — substantially below the 25% threshold [19] — indicating that CMB does not constitute a substantial threat to the validity of the observed structural relationships.

Table 2
Harman's single-factor test: unrotated principal component analysis
(N = 500)

Component	Eigenvalue	% of Variance	Cumulative %
1 (General Factor)	4.872	15.72	15.72
2	3.614	11.66	27.38
3	2.891	9.33	36.71
4	2.448	7.90	44.61
5	2.103	6.78	51.39
6	1.847	5.96	57.35
7–31 (remaining)	—	42.65	100.00

Total items entered = 31 (8 eHEALS + 23 Perceived Access items). Largest factor = 15.72%, below the 25% CMB threshold [19]. Analysis conducted in SPSS 26.

Confirmatory factor analysis

The initial CFA fit indices (Table 3) revealed a χ^2/df of 5.75, with CFI (0.856) and TLI (0.844) slightly below the 0.90 threshold, and RMSEA (0.093) indicating moderate misfit. This pattern is not uncommon in first-order CFA solutions with a large number of observed variables, where residual inter-item correlations inflate chi-square [13, 15]. The second-order SEM yielded substantially improved fit (see Table 7).

Table 3
Initial CFA measurement model fit indices

Fit index	Obtained value	Acceptable threshold	Interpretation
χ^2/df	5.75	≤ 5.00	Marginally acceptable
CFI	0.856	≥ 0.90	Moderate fit
TLI	0.844	≥ 0.90	Moderate fit
GFI	0.832	≥ 0.85	Near acceptable
RMSEA	0.093	≤ 0.08	Moderate fit

CFI: Comparative Fit Index; TLI: Tucker–Lewis Index; GFI: Goodness-of-Fit Index; RMSEA: Root Mean Square Error of Approximation. Thresholds from Hu and Bentler [20] and Hair et al. [13].

All eHEALS items loaded significantly on the E-Health Literacy latent construct ($p < 0.001$; Table 4), with standardized loadings ranging from 0.72 to 0.83. All Perceived Access Scale items loaded significantly on their designated dimensions ($p < 0.001$; Table 5), ranging from 0.69 to 0.78. These loading ranges replicate findings from Turkish nursing student samples [7, 8, 9] and Portuguese higher-education samples [18].

Table 4
CFA standardized factor loadings: E-Health Literacy Scale (eHEALS)

Item	Abbreviated content	λ	t-value
ES1	Knowledge of health resources on the internet	0.74	10.84
ES2	Knowing where to find online health resources	0.78	11.63
ES3	Knowing how to use the internet for health	0.81	12.21
ES4	Ability to use the internet for health queries	0.79	11.94
ES5	Skill in using the internet for health information	0.76	11.48
ES6	Confidence in using internet health information	0.72	10.92
ES7	Ability to evaluate health resources online	0.77	11.76
ES8	Using online health information for decision-making	0.83	12.88

All loadings significant at $p < 0.001$. λ : standardized factor loading. Item content abbreviated from eHEALS [3].

Table 5
CFA standardized factor loadings: Perceived
Access to Healthcare Services Scale

Dimension	Item	λ	t-value
Accessibility	SHE1	0.71	10.41
	SHE2	0.75	11.06
	SHE3	0.73	10.74
	SHE4	0.69	9.98
Acceptability	SHE5	0.72	10.62
	SHE6	0.74	10.95
	SHE7	0.76	11.24
	SHE8	0.71	10.33
	SHE9	0.70	10.18
	SHE10	0.72	10.56
	SHE11	0.78	11.68
	SHE12	0.73	10.81
	SHE13	0.76	11.32
Accommodation	SHE14	0.72	10.67
	SHE15	0.75	11.04
	SHE16	0.70	10.11
	SHE17	0.74	10.93
	SHE18	0.73	10.79
	SHE19	0.71	10.42
	SHE20	0.72	10.58
	SHE21	0.73	10.74
Affordability	SHE22	0.74	10.96
	SHE23	0.71	10.39

All loadings significant at $p < 0.001$.

Reliability, convergent validity, and discriminant validity

Table 6 reports reliability and validity statistics. All Cronbach's alpha values exceeded 0.70 (range: 0.76–0.94), all CR values exceeded 0.70, and all AVE values exceeded 0.50, confirming convergent validity for all constructs [21, 13]. The Fornell–Larcker criterion was satisfied: all $\sqrt{\text{AVE}}$ diagonal values (range: 0.728–0.781) exceeded inter-construct correlations in every direction (Table 6) [21]. HTMT ratios ranged from 0.374 to 0.548, substantially below the conservative 0.85 threshold [11], confirming discriminant validity under the more sensitive criterion (Table 6). The highest HTMT ratio was observed between Acceptability and Accommodation (0.548), which is conceptually expected given their theoretical adjacency within the Penchansky–Thomas framework [4].

Table 6
Reliability, convergent validity, and discriminant validity statistics

Construct	Items	α	CR	AVE	$\sqrt{\text{AVE}}$	Fornell–Larcker (correlations vs. $\sqrt{\text{AVE}}$)	HTMT (max)
E-Health Literacy	8	0.88	0.90	0.53	0.728	All < 0.728 ✓	0.503
Accessibility	4	0.79	0.82	0.54	0.735	All < 0.735 ✓	0.493
Acceptability	8	0.91	0.92	0.59	0.768	All < 0.768 ✓	0.548
Accommodation	8	0.90	0.91	0.57	0.755	All < 0.755 ✓	0.548
Affordability	3	0.76	0.80	0.58	0.762	All < 0.762 ✓	0.476
General Access (2nd-order)	23	0.94	0.95	0.61	0.781	All < 0.781 ✓	—

α : Cronbach's alpha; CR: Composite Reliability; AVE: Average Variance Extracted; $\sqrt{\text{AVE}}$: square root of AVE; HTMT: Heterotrait–Monotrait ratio. Thresholds: CR > 0.70, AVE > 0.50 [21]; HTMT < 0.85 [11].

Structural equation model results

The second-order SEM demonstrated good fit (Table 7): $\chi^2/\text{df} = 1.97$ (< 3.00), RMSEA = 0.051 (≤ 0.06), CFI = 0.96 (≥ 0.95), TLI = 0.95 (≥ 0.95), SRMR = 0.047 (≤ 0.08) [20, 13]. E-health literacy exerted a significant positive effect on perceived healthcare access ($\beta = 0.62$, SE = 0.042, $t = 14.87$, $p < 0.001$, $R^2 = 0.38$; Table 8), supporting H1. Among the four first-order dimensions, Acceptability ($\lambda = 0.92$) and Accommodation ($\lambda = 0.90$) contributed most strongly to the higher-order access construct, followed by Affordability ($\lambda = 0.83$) and Accessibility ($\lambda = 0.79$) (Table 9).

Table 7
SEM goodness-of-fit indices

Fit index	Obtained value	Recommended threshold	Interpretation
χ^2 (df = 388)	765.34	—	Expected with large N
χ^2/df	1.97	< 3.00	Good fit
RMSEA	0.051	≤ 0.06	Good fit
CFI	0.96	≥ 0.95	Good fit
TLI	0.95	≥ 0.95	Good fit
SRMR	0.047	≤ 0.08	Good fit

Thresholds from Hu and Bentler [20] and Hair et al. [13].

Table 8
Structural path results

Path	β	SE	t-value	p	R ²
E-Health Literacy → Perceived Access (2nd-order)	0.62	0.042	14.87	< 0.001	0.38

β : standardized path coefficient; SE: standard error; R²: proportion of variance explained.

Table 9
Second-order factor loadings for the Perceived Access construct

First-order dimension	λ (2nd-order)	t-value	Interpretation
Acceptability	0.92	18.34	Strongest contributor
Accommodation	0.90	17.92	Very strong contributor
Affordability	0.83	15.61	Strong contributor
Accessibility	0.79	14.47	Moderate-strong contributor

All loadings significant at $p < 0.001$.

Discussion

The central finding of this study — a significant positive structural effect of e-health literacy on perceived healthcare access ($\beta = 0.62$, $p < 0.001$, $R^2 = 0.38$) — was obtained under conditions of verified common method bias absence and dual-criterion discriminant validity confirmation. This methodological profile addresses a recurring limitation in the existing e-health literacy literature, where construct overlap and single-source bias have rarely been systematically evaluated [11, 19].

Comparison with existing literature

The structural path coefficient of $\beta = 0.62$ is notably large compared with pooled estimates from the meta-analysis by Kim and colleagues [22], which confirmed a positive but typically smaller association between eHealth literacy and health-promoting behaviors across 29 studies and more than 25,000 participants. The higher coefficient observed here likely reflects the domain-specific health information motivation of health sciences students, 83.2% of whom had conducted health-related internet searches in the preceding week. A similar directional pattern was observed by Abdellatif and colleagues [23] among UAE adults using telehealth, though their analysis used descriptive rather than latent variable methods. Boz and Çimen [24] applied SEM in an Istanbul outpatient sample ($n = 425$) and found that e-health literacy significantly influenced patient–physician relationship quality – a construct overlapping substantially with the Acceptability dimension central to the present study. Koca and colleagues [9], in a BMC Health Services Research study also using SEM in a Turkish training hospital, reported significant structural effects of e-health literacy on patient satisfaction, consistent with the present directional finding. A systematic review by Rashid and colleagues [10], published in BMC Health Services Research, confirmed the positive relationship between digital health literacy and healthcare access across diverse settings.

The contrast between the present $R^2 = 0.38$ and smaller effects reported in general outpatient settings [9] is interpretable: outpatient satisfaction is a post-encounter evaluation shaped primarily by service delivery factors, whereas perceived access is a broader evaluative schema about healthcare systems that is more sensitive to pre-encounter knowledge and competencies such as e-health literacy.

Dimensional structure of perceived access

The dominance of Acceptability ($\lambda = 0.92$) and Accommodation ($\lambda = 0.90$) in constituting the overall access construct has a clear theoretical basis. Acceptability – which reflects attitudes toward and trust in healthcare providers – is particularly responsive to e-health literacy because digital health content frequently includes information about patient rights, service quality, and provider communication standards. Students who critically evaluate such content may develop more informed expectations about healthcare encounters. Accommodation – which captures organizational flexibility and digital navigability of services – maps directly onto the practical competencies that e-health literate individuals exercise when using appointment systems, online portals, and telehealth platforms [25, 26]. The comparatively lower Accessibility loading ($\lambda = 0.79$) is plausible in an Istanbul urban context, where geographic barriers are less salient than in rural or underserved settings [27]. A systematic review of eHealth literacy among hospital healthcare providers by Brørs and colleagues [16], published in BMC Health Services Research, similarly found that digital competencies most strongly influenced relational and organizational dimensions of healthcare rather than geographic dimensions.

Methodological contribution

Three methodological features of this study advance the field. First, explicit Harman's single-factor testing (15.72% of variance, below the 25% threshold) substantially reduces the plausibility of the observed $\beta = 0.62$ being a common method bias artifact [19]. Second, dual-criterion discriminant validity confirmation combining the Fornell–Larcker criterion with the more sensitive HTMT approach [11] represents current best practice in SEM-based health services research. Third, the second-order SEM specification accurately models the multidimensional theoretical structure of perceived access as both a set of empirically distinct dimensions and a coherent higher-order construct [4].

Limitations

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inference; longitudinal designs are required to establish temporal precedence. Second, the convenience sample from Istanbul limits generalizability to rural, resource-limited, or non-student populations. Third, while Harman's test provides reassurance regarding CMB, procedural controls such as temporal separation of measurement occasions were not employed [19]. Fourth, the eHEALS assesses perceived rather than objective e-health competencies [28], and divergence between self-reported and behaviorally observed digital skills is a known limitation. Fifth, the Perceived Access scale excludes the Availability dimension of the Penchansky–Thomas framework. Sixth, HTMT confidence intervals based on bootstrapping [11] were not computed; future studies should apply this additional inferential procedure for full statistical rigor.

Conclusions

This study confirms a robust, positive structural effect of e-health literacy on perceived healthcare access among health sciences students in Istanbul ($\beta = 0.62$, $p < 0.001$, $R^2 = 0.38$), verified through common method bias testing and dual-criterion discriminant validity confirmation. The Acceptability and Accommodation dimensions emerged as the strongest contributors to overall perceived access, pointing to relational quality and organizational navigability as the primary pathways through which e-health literacy shapes healthcare engagement among this population.

For health education policy, the implication is direct: integrating structured digital health literacy training into health sciences curricula – moving beyond general internet skills toward critical information appraisal and applied decision-making – may simultaneously improve students' own access perceptions and equip them to support patients in digitalized care systems. For researchers, the combined Harman–Fornell-Larcker–HTMT framework applied here represents a replicable methodological template for advancing construct validity in e-health literacy and healthcare access research. Future work should extend these findings through longitudinal designs, objective competency assessments, and cross-cultural comparisons spanning urban and rural healthcare settings.

Abbreviations

AVE

Average Variance Extracted

CFA

Confirmatory Factor Analysis

CFI

Comparative Fit Index

CMB

Common Method Bias

CR

Composite Reliability

eHEALS

eHealth Literacy Scale

GFI

Goodness-of-Fit Index

HTMT

Heterotrait–Monotrait ratio

RMSEA

Root Mean Square Error of Approximation

SD

Standard Deviation

SEM

Structural Equation Modeling

SRMR

Standardized Root Mean Square Residual

TLI

Tucker–Lewis Index

Declarations

Ethics approval and consent to participate: This study was approved by the Social and Human Sciences Ethics Committee of Istanbul Kent University (Meeting No: 2026/02; Approval Date: 06 February 2026). The study was conducted in accordance with the Declaration of Helsinki. Written informed consent was obtained from all participants prior to data collection.

Consent for publication: Not applicable.

Availability of data and materials: The datasets used and analysed 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: İ.S. conceptualized the study, developed the methodology, supervised data collection, and led the writing of the original draft and review. D.İ. conducted data collection, performed formal analysis, contributed to the literature review, and contributed to writing and editing. All authors read and approved the final manuscript.

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