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The Relationship Between Academicians' Health Literacy and Artificial Intelligence Literacy: The Sample of Türkiye

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ABSTRACT

This research study aimed to determine academicians' levels of the Health Literacy (HL) and Artificial Intelligence Literacy (AI-L), and the factors associated with these competencies. A cross-sectional, correlational study design was conducted. The sample comprised 417 academicians working at various universities across Türkiye who participated between 6 June and 29 July 2025. Data were collected using a personal information form, the European Health Literacy Survey-Short Form, and the Artificial Intelligence Literacy Scale. More than half of the participants reported internet use of 5 h or more per day; 89.0% used AI applications. Overall, 34.3% of participants fell into the problematic/limited or inadequate categories for HL. The mean score on the HL Scale was 83.0 ± 18.9, and the mean score on the AI-L Scale was 46.9 ± 6.6. Health literacy scores were higher among females, single-living individuals, and academicians working in health-related fields. Mean AI-L scores were lower among those with the academic ranks of associate professor and professor, among participants who reported only moderate ability to use information technology tools, and among those who did not use AI applications or were ambivalent about their usefulness. A weak positive correlation was observed between HL and AI-L scale mean scores. The findings indicate that HL and AI-L are positively but weakly associated, suggesting that they represent related but distinct competencies. Further longitudinal and intervention studies are needed to clarify the relationship between these competencies and evaluate approaches to their development.

1 | Introduction

Improving health literacy (HL) has increasingly become a public-health priority and is recognized as a determinant of health (Sørensen et al. 2012). HL is defined as the ability to obtain, understand, appraise, synthesize, communicate, and apply health-related information, utilizing general literacy skills such as reading, writing, numeracy, listening and speaking (Liu et al. 2020). HL levels vary by country; countries in Southern, Western, and Eastern Europe generally score lower than Northern Europe (Baccolini et al. 2021). In Türkiye, 21.0% of the population have inadequate HL, and 32.9% have problematic/limited HL (Republic of Türkiye Ministry of Health 2024). These findings underscore the need to raise HL at the population level.

Interventions to raise HL include educational programs (Budak and Ozkan 2021), lifestyle interventions (Nawabi et al. 2022), simplified language services, and intensive community-based

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programs (Pleasant et al. 2017). In addition, internet-, technology-, AI- and robotics-based interventions can be leveraged to improve HL (Asiksoy 2025; Chu et al. 2022; Shehab et al. 2024; Vallurupalli et al. 2025). Recent evidence suggests that AI is being used increasingly across many domains and may contribute to improving HL (Asiksoy 2025; Chu et al. 2022; Shehab et al. 2024; Vallurupalli et al. 2025).

As academic interest in AI's impact on healthcare grows, there is an increased need for comprehensive roadmaps for scientific research focused on AI use in healthcare, and trends toward AI adoption in health services have accelerated (Shah et al. 2024). This trend foregrounds the importance of artificial intelligence literacy (AI-L) for the effective and responsible use of AI (Song et al. 2025). AI-L remains an emerging research area (Almatrafi et al. 2024), and identifying the factors that influence AI-L has been recommended (Zhang et al. 2025).

Given the influence of HL on health behaviours (Chantaranamchoo et al. 2025), universities have an important role in promoting health literacy and fostering healthy-living cultures among academic staff (Melnyk et al. 2023). Academicians are highly educated professionals engaged in research and teaching (Kartal et al. 2022), and owing to their positions, knowledge, skills, behaviours and advanced education, they constitute a group that can exert critical influence on society (Isik et al. 2025). Academicians contribute to advancing science through their research and play an important role in developing and sustaining HL in the lives of their students and broader communities. To promote HL and support informed decision-making among university personnel, academicians must be able to use health information effectively (Chantaranamchoo et al. 2025). However, the university work environment is characterized not only by a largely sedentary nature but also by elements of physical and mental stress (Okafor et al. 2021). University academic staff may face substantial health risks due to this sedentary work environment, physiological stress, and long working hours (Ali et al. 2023; Husaema et al. 2025). Although higher education levels generally enhance health literacy (Orsal et al. 2021), it is essential to understand how academics—given their advanced education and professional roles—comprehend, utilize, and critically evaluate health-related information when using health tools and artificial intelligence, and how they protect themselves against misinformation. While academics are often assumed to have easy access to information, the specific ways in which they access and apply health information—and whether they turn to unreliable digital sources or critically evaluate information obtained via artificial intelligence—are matters of importance, particularly given their roles as role models and guides for both society and their students (Kartal et al. 2022).

Given academicians' roles as educators and societal role models, examining HL and AI-L together is important. In particular, understanding the relationship between these competencies and identifying their associated factors may provide insights into how academicians evaluate and use health-related information obtained through artificial intelligence. The rationale for examining these competencies together can be understood through Nutbeam's Health Literacy Model (Nutbeam 2000) and the Technology Acceptance Model (TAM) (Marangunić and Granić 2015; Taherdoost 2018). While Nutbeam's model emphasizes the skills required to access, understand, and critically evaluate health information, TAM explains technology acceptance in terms of perceived usefulness, perceived ease of use, and attitude toward use. Limited HL and AI-L may hinder individuals' ability to critically evaluate AI-generated health information, potentially leading to its uncritical acceptance or rejection (Tzortzatou Nanopoulou 2026). Although HL is essential for health promotion and disease prevention, studies examining HL among academicians in Türkiye remain limited (Kartal et al. 2022; Ugur and Guder 2021). However, to the best of our knowledge, no study has simultaneously examined HL and AI-L among academicians in Türkiye or investigated the relationship between these competencies and their associated factors. Therefore, this study aimed to determine academicians' levels of HL and AI-L and identify factors associated with these competencies. Research questions:

1. What are the levels of health literacy and AI-L among academicians?
2. What is the relationship between academicians' health literacy and AI-L levels?
3. Are the sociodemographic characteristics of academics associated with their health literacy and AI-L levels?

2 | Methods

2.1 | Design

The study employed a cross-sectional, correlational design.

2.2 | Participants

The target population comprised 185,898 academicians employed at universities across Türkiye (https://istatistik.yok.gov.tr). The investigators attempted to invite academicians from universities across Türkiye; however, participation was voluntary and self-selected through an online survey. Therefore, the final sample represents a non-probability voluntary response sample. Because participation was voluntary, a minimum sample size for a finite population was calculated. According to the results of the power analysis conducted in the study using the G*Power 3.1.9.7 program to determine the sample size, for the regression model with 23 variables, assuming an effect size of $f^2 = 0.09$, a Type 1 error of 0.05, and a power of 0.95, the required sample size was determined to be at least 377. The study was completed with 417 voluntary participants. Although the achieved sample exceeded the calculated minimum sample size, this does not eliminate the potential for selection bias associated with voluntary participation. Inclusion criteria were current employment as an academic and consent to participate. Exclusion criteria included the presence of a neuropsychiatric disorder; removal from the study occurred if data collection instruments were filled out incompletely.

2.3 | Data Collection Instruments

Data were collected using a 'Personal Information Form', the 'European Health Literacy Survey—Short Form', and the 'Artificial Intelligence Literacy Scale.'

Personal Information Form: Developed by the researchers based on the literature (Terzi et al. 2024; Dogan and Cetinkaya 2019), the form contained 21 items covering participants' age, gender, marital status, income level, presence of chronic disease, self-rated health, working duration and questions on internet and AI use.

European Health Literacy Survey-Short Form: Developed by the European Health Literacy Consortium and adapted into Turkish by Terzi et al. (2024), this 12-item, unidimensional Likert-type scale uses response options '1 = very difficult, 2 = difficult, 3 = easy, 4 = very easy, 99 = I don't know'. Only responses 1–4 are considered valid and included in score computation. The scale's total score is calculated as the proportion of items answered 'easy' or 'very easy' divided by the number of valid responses, multiplied by 100 to yield a percentage. Scores are categorized into four groups: excellent, sufficient, problematic/limited, and inadequate. The Turkish validation in an adult population (min. 18–max. 61 years; mean: 30.17 ± 10.37) reported a Cronbach's alpha of 0.886 (Terzi et al. 2024). In the present study, Cronbach's alpha was 0.881.

Artificial Intelligence Literacy Scale: Developed by Wang et al. (2023), this 12-item scale assesses individuals' knowledge about AI, usage skills and ethical awareness. The Turkish adaptation of the scale was conducted by Polatgil and Guler (2023). The scale comprises four subdimensions—awareness, usage, appraisal and ethics—and is rated on a five-point Likert scale: (1) strongly disagree, (2) disagree, (3) neither agree nor disagree, (4) agree, (5) strongly agree. Total scores range from 12 to 60. Polatgil and Guler (2023) reported a Cronbach's alpha of 0.939; in this study, Cronbach's alpha was 0.829.

2.4 | Data Collection Procedure

Data collection began after institutional ethics approval was obtained and took place between 6 June and 29 July 2025. To recruit academicians throughout Türkiye, researchers sent official letters from their university, including their own institution, to universities across Türkiye, attaching the study link to an online survey created using Google Forms. Universities that agreed to participate were asked to share the survey link with their academicians and invite voluntary participation. Because dissemination depended on participating institutions and participation was voluntary, the study used a non-probability voluntary response sampling approach. Academicians who consented clicked an 'I agree to participate in the study' checkbox located below the study information before accessing the survey items. Completion time for the instruments was approximately 15–20 min. Two weeks after the final survey, the study was concluded on 12 August 2025.

2.5 | Data Analysis

Data were analysed using IBM SPSS 22. Descriptive statistics (frequency, percentage, mean, standard deviation, minimum, maximum), nonparametric tests (Mann–Whitney *U*, Kruskal–Wallis), Spearman's correlation, and multiple linear regression analysis were used. The Shapiro–Wilk test assessed normality. Mann–Whitney *U* was used to compare two groups' mean scores on the AI-L and HL scales; Kruskal–Wallis was used for comparisons among three or more groups. Dunn's test with Bonferroni correction for multiple comparisons was used to adjust the significance level and adjust for the Type I error rate for post hoc pairwise comparisons after significant Kruskal–Wallis tests. Effect size was calculated as Rank-Biserial Correlation (*r*) for the Mann–Whitney *U*-test and as ordinal Eta-Squared (η^2_H) for the Kruskal–Wallis test. Factors predicting the participants' AI-L and HL were analysed by independently developed multiple linear regression models. Since the critical assumptions underlying the models established for AI-L and HL—namely, homogeneity of variance and independence of errors—were fully satisfied, the findings obtained from the AI-L and HL regression models have been accepted as valid and reliable. Spearman's correlation analysed relationships between AI-L and HL scores both without and with controlling for variables thought to influence that relationship. Statistical significance was set at $p < 0.05$.

2.6 | Ethical Considerations

Ethical approval was granted by Ankara Yıldırım Beyazıt University Ethics Committee of Health Sciences (22.05.2025, 05-1313). Institutional permissions were requested from all universities in Türkiye, and institutions that agreed were asked to share the online survey with their academicians. The goal of the study was explained to participants before they filled out the online form, and they were asked to tick the 'confirmation checkbox' to show their agreement. The scales were used after obtaining permission.

3 | Results

The majority of the participants (66.9%) were females, 62.6% were married, 90.9% were part of a nuclear family, 89.7% had lived in a city for most of their lives, and 47.2% reported their income was equivalent to their expenses. The mean age was 40.2 years. Academically, 67.4% held a doctoral degree and 30.7% were assistant professors, and 42.9% worked in health-related faculties. Regarding health status, two-thirds (65.0%) rated their health as 'good', and 28.1% indicated they had a condition requiring continuous follow-up. Participants reported obtaining health-related information predominantly from health professionals (90.4%), scientific studies/literature (65.9%), and the internet (62.3%). More than half (55.6%) rated their ability to use information technology tools as 'good'; 53.0% used the internet 5 h or more per day. The internet was mainly used for research (98.3%), browsing social media (77.9%), and watching videos (58.7%). Regarding AI applications, a large majority (89.0%) used AI applications, and 84.7% found AI applications useful. The most frequently used AI

TABLE 1 | Descriptive characteristics of the participants ($n = 417$).

Variable	Group	*n*	%
Gender	Female	279	66.9
	Male	138	33.1
Age[a]	18–24	7	1.7
	25–34	114	27.3
	35–44	175	42.0
	45–54	78	18.7
	55–64	36	8.6
	> 65	7	1.7
Marital status	Single	136	32.6
	Married	261	62.6
	Spouse deceased/divorced	20	4.8
Family type	Nuclear family	379	90.9
	Extended family	22	5.3
	Living alone	16	3.8
Place where most of the life was spent	City	374	89.7
	Town	35	8.4
	Village	8	1.9
Income status	Income greater than expenses	131	31.4
	Income equal to expenses	197	47.2
	Income less than expenses	89	21.3
Educational level	Bachelor's degree	19	4.6
	Master's degree	117	28.1
	Doctorate	281	67.4
Faculty (workplace)	Faculty of Health Sciences/Nursing/Medicine/Dentistry	179	42.9
	Faculty of Humanities and Social Sciences/ Education/Arts and Sciences	67	16.1
	Vocational Schools (Health and Technical)	52	12.5
	Faculty of Engineering/Architecture	26	6.2
	Vocational School (other)	17	4.1
	Faculty of Law/Political Sciences/Economics and Administrative Sciences	13	3.1
	Faculty of Islamic Studies/Theology	11	2.6
	Faculty of Sport Sciences	9	2.2
	Faculty of Fine Arts/Conservatory	8	1.9
	Agriculture/Forestry/Veterinary/Fisheries	8	1.9
	School of Foreign Languages	6	1.4
	Other	21	5.0

(Continues)

TABLE 1 | (Continued)

Variable	Group	*n*	%
Academic title	Research assistant	70	16.8
	Research assistant (PhD)	23	5.5
	Lecturer	62	14.9
	Lecturer (PhD)	35	8.4
	Assistant professor	128	30.7
	Associate professor	51	12.2
	Professor	48	11.5
Health status	Very good	40	9.6
	Good	271	65.0
	Moderate	98	23.5
	Poor	8	1.9
Presence of disease requiring continuous follow-up/ treatment	Yes	117	28.1
	No	300	71.9
Where do you obtain health information?[b]	Health professionals (physician, nurse, pharmacist, etc.)	377	90.4
	Scientific studies/literature	275	65.9
	Internet	260	62.3
	Books	112	26.8
	The mass media (television, radio, newspaper)	95	22.7
	Family members or friends	94	22.5
	Health related courses	72	17.2
	Other	12	2.0
Skill level in using information technology tools	Moderate	56	13.4
	Good	232	55.6
	Very good	129	30.9
Daily internet use time	0–2 h	34	8.2
	3–4 h	162	38.8
	5 h and above	221	53.0
For what purposes do you use the Internet?[b]	Research	410	98.3
	Social media	325	77.9
	Watching videos	245	58.7
	Listening to music	230	55.1
	Studying	211	50.5
	Chatting	180	43.1
	Games	60	14.3
	Other	32	7.0
Use of AI applications	Yes	371	89.0
	No	46	11.0

(Continues)

TABLE 1 | (Continued)

Variable	Group	*n*	%
AI applications used[b]	General-Purpose AI Chatbots (ChatGPT, Gemini, DeepSeek, Microsoft Copilot, Grok)	368	88.2
	Specialized academic and literature tools (Scite AI, Elicit, SciSpace, NotebookLM, Chatpdf, Concensus, Perplexity, Piri AI, Research Rabbit, Connected Papers)	55	13.1
	AI writing and text editing assistants (Quillbot, DeepL, Grammarly, Thesify)	49	11.7
	AI presentation and visual content generators (Gamma AI, DALL-E, Canva, Napkin AI, Flourish, Midjourney)	40	9.5
	Diğer (Norton AI, Monica, Suno, Claude, Synthesia, Aria, Cursor)	13	3.1
Do you find AI applications useful?	Yes	353	84.7
	No	9	2.2
	Undecided	55	13.2
Purpose of using AI applications[b]	Information/idea generation	338	81.0
	Research	298	71.4
	Education	203	48.6
	Personal assistant	151	36.2
	Content creation	80	19.1
	Entertainment	57	13.6
	Other	13	3.1
Age	$\bar{x}$: 40.2 ± 9.8, Min: 23, Max: 76		
Total years worked	$\bar{x}$: 16.0 ± 9.9, Min: 0.1, Max: 50.0		
Total years worked as an academician	$\bar{x}$: 11.2 ± 9.0, Min: 0.1, Max: 45		

Abbreviations: %, percent; Max, maximum; Min, minimum; *n*, number; $\bar{x}$, mean.
[a]Age grouping was made according to the age categories used in the Republic of Turkey Ministry of Health report 'Turkiye Health Literacy Level and Related Factors'.
[b]Multiple responses were allowed.

applications were general-purpose AI chatbots (%88) (ChatGPT, Gemini, DeepSeek, Microsoft Copilot, Grok) and specialized academic and literature tools (%13.1) (Scite AI, Elicit, SciSpace, NotebookLM, Chatpdf, Concensus, Perplexity, Piri AI, Research Rabbit, Connected Papers); primary uses included information gathering/idea generation (81%), research (71.4%), and education (48.6%). Descriptive data for participants are presented in detail in Table 1.

The mean HL score was 83.0 ± 18.9 (Table 2). Categorically, 28.3% of participants had 'excellent' HL, 37.4% 'sufficient', 25.2% 'problematic/limited', and 9.1% 'inadequate'. Gender, family type, faculty of employment, and perceived health status were significantly associated with HL scale scores ($p < 0.05$). Females, single-living individuals, and those reporting 'very good' perceived health had statistically significantly higher HL mean scores ($p < 0.05$). Academicians working in health-related faculties had higher HL scores than those in Faculties of Humanities and Social Sciences/Education/Arts and Sciences, Engineering/Architecture, and Agriculture/Forestry/Veterinary/Fisheries. Additionally, academicians in health and technical vocational schools had higher HL scores than those in Engineering/Architecture and Agriculture/Forestry/Veterinary/Fisheries faculties ($p < 0.05$). The effect sizes were computed as $r = 0.14$ for gender, $\eta^2_H = 0.03$ for family type, $\eta^2_H = 0.02$ for faculty, and $\eta^2_H = 0.02$ for perceived health status (Table 3). The computed effect size coefficients indicate that these variables have a small effect on HL in practical terms.

A multiple linear regression analysis was performed to determine the independent variables affecting participants' Health Literacy (HL), while controlling for possible confounding factors. The regression model demonstrated statistically significant predictive power overall ($F = 2.477$, $p = 0.001$). An examination of the model's coefficient of determination ($R^2 = 0.090$) revealed that the independent variables included in the model collectively explained 9.0% of the total variance in HL. When the independent effects of the variables within the model were analysed, it was found that—even after controlling for the effects of all other demographic and theoretical factors—age group ($\beta = 3.734$, $t = 0.294$, $p = 0.022$), gender ($\beta = -5.146$, $t = -2.520$, $p = 0.012$), family type ($\beta = 5.063$, $t = 2.347$, $p = 0.019$), and health status ($\beta = -5.634$, $t = -3.533$, $p < 0.001$)

TABLE 2 | Distribution of Health Literacy Scale (HL-S), Artificial Intelligence Literacy Scale (AIL-S), and subdimension scores.

Scale	Score type	$\bar{x}$	SD	Min	Max
HL-S	Total	83.0	18.9	0	100
AIL-S	Total	46.9	6.6	19	60
	Awareness subdimension	11.7	1.9	4	15
	Usage subdimension	11.4	2.2	3	15
	Appraisal subdimension	11.5	2.1	3	15
	Ethic subdimension	12.1	2.3	4	15

Abbreviations: AIL-S, Artificial Intelligence Literacy Scale; HL-S, Health Literacy Scale; Max, maximum; Min, minimum; SD, standard deviation; $\bar{x}$, mean.

were statistically independent and significant determinants of Health Literacy (Table 4).

The mean AI-L score was 46.9 ± 6.6 (Table 2). Subdimension means were: Awareness 11.7 ± 1.9, Usage 11.4 ± 2.2, Appraisal 11.5 ± 2.1, and Ethics 12.1 ± 2.3. AI-L scores were associated with age, academic rank, perceived health status, ability to use information technology tools, AI application usage, and perceived usefulness of AI ($p < 0.05$). Participants aged 25–34 had higher AI-L means than those aged 45–54 and 55–64; participants aged 35–44 had higher AI-L means than those aged 55–64 ($p < 0.05$). However, the calculated effect size coefficient ($\eta^2_H = 0.01$) indicates that age variable has a small effect on AI-L at a practical level. Academicians with the ranks of associate professor and professor had significantly lower AI-L mean scores ($p < 0.05$). Conversely, academicians holding the title of doctoral lecturers/researchers had significantly higher AI-L means than lecturers and assistant professors ($p < 0.05$). The effect size coefficient calculated for the academic title variable ($\eta^2_H = 0.04$) indicates that it has a small effect on AI-L at a practical level. Participants who rated their health as 'very poor', those reporting only moderate ability to use information technology tools, those who did not use AI applications, and those who were ambivalent about the usefulness of AI applications had significantly lower AI-L mean scores ($p < 0.05$). The effect size coefficients calculated for these variables revealed that a health status has a small effect ($\eta^2_H = 0.02$), the ability to use information technology tools has a large effect ($\eta^2_H = 0.21$), usage of artificial intelligence applications has a medium effect ($r = 0.33$), and the perception of artificial intelligence applications as useful has a medium effect ($\eta^2_H = 0.07$) on AI-L at practical level (Table 3).

Multiple linear regression analysis was conducted to identify the independent factors influencing participants' artificial intelligence literacy (AI-L) while controlling for potential confounding effects. The regression model demonstrated statistically significant predictive power overall ($F = 11.68$, $p < 0.001$). An examination of the model's coefficient of determination ($R^2 = 0.319$) revealed that the independent variables included in the model collectively explained 31.9% of the total variance in artificial intelligence literacy. The independent effects of the variables within the model were analysed. Even after controlling for the effects of all other demographic and theoretical factors, the variables of health status ($\beta = -1.178$, $t = -2.447$, $p = 0.015$), information technology usage skills ($\beta = 3.730$, $t = 8.090$, $p < 0.001$), use of artificial intelligence tools ($\beta = -4.978$, $t = -4.770$, $p < 0.001$), and perceived usefulness of artificial intelligence applications ($\beta = -1.124$, $t = -2.346$, $p = 0.020$) were found to be statistically independent and significant determinants of artificial intelligence literacy (Table 4).

Correlational analysis evaluated relationships among the HL scale, the AI-L scale, and the AI-L subdimensions. In the initial analysis, no variables that could affect these relationships were controlled for. A weak positive and statistically significant correlation was found between HL and AI-L total scores ($p < 0.001$, $r = 0.270$; weak correlation). Additionally, HL correlated positively and significantly with the AI-L Awareness subdimension ($p = 0.004$, $r = 0.141$; very weak correlation), Usage subdimension ($p = 0.001$, $r = 0.159$; very weak correlation), Appraisal subdimension ($p < 0.001$, $r = 0.204$; weak correlation), and Ethics subdimension ($p < 0.001$, $r = 0.266$; weak correlation). Subsequently, the analysis was repeated while controlling for the 'health status' variable—which was found to affect both HL and AI-L scores—as well as the variables of age, education, academic title and faculty of employment, which were theoretically considered capable of influencing the relationship between HL and AI-L. It was observed that the positive relationship between the HL Scale, the AI-L Scale, and the sub-dimension scores of the AI-L Scale remained significant even after the effects of these variables were controlled for (Table 5).

4 | Discussion

Health literacy is a multidimensional construct encompassing the skills needed to obtain, understand, appraise, and apply health-related information (Sørensen et al. 2012). In an era of rapidly expanding digital health resources, HL is a core competency not only for patients but also for academicians and health professionals who deliver care (Almatrafi et al. 2024; Chantaranamchoo et al. 2025). Academicians, due to their high educational attainment, access to international knowledge, and technology use skills, are an early and effective source of information and thus occupy a pivotal role in accessing health information and educating students and communities (Chantaranamchoo et al. 2025; Dogan and Cetinkaya 2019). In this study, more than half of academicians demonstrated sufficient or excellent HL (37.4% and 28.3%, respectively), while a substantial minority showed problematic/limited (25.2%) or inadequate (9.1%) HL. Given the association between HL and higher education (Republic of Türkiye Ministry of Health 2024), the relatively favourable HL distribution observed in this highly educated population is consistent with expectations. Nevertheless, considerable proportions of academicians with problematic/limited or inadequate HL align with findings in the literature. For example, Kartal et al. (2022) reported a mean HL of 70.4 ± 15.2 among academicians, with 32% classified as 'limited' or 'inadequate', and Dogan and Cetinkaya (2019) found that 40% of academicians had limited or inadequate HL. Because academicians are active users of various information sources and play important roles in promoting healthy behaviours, it is desirable that all academicians possess adequate HL. Roe

TABLE 3 | Comparison of Artificial Intelligence Literacy Scale (AIL-S) and Health Literacy Scale (HL-S) scores by variables.

		AIL-S				HL-S			
Variable	**Group**	**Med**	**Q1–Q3**	$\bar{x}$	**Test stats**	**Med**	**Q1–Q3**	**x**	**Test stats**
Gender	Female	47.0	43.0–51.0	46.7	$p=0.587$* Z: −0.543	92.0	75.0–100.0	84.3	**$p=0.005$*** Z: −2.787 $r=0.14$
	Male	47.5	43.0–51.0	47.2		83.0	71.5–92.0	80.3	
Age*	18–24 (a)	46.0	40.0–51.0	46.2	**$p=0.028$**** χ^2: 12.524 $\eta^2_H=0.01$ b > e, d c > e	83.0	83.0–92.0	85.1	$p=0.894$** χ^2: 1.162
	25–34 (b)	48.0	44.0–53.0	48.1		92.0	67.0–100.0	81.9	
	35–44 (c)	47.0	44.0–51.0	47.3		92.0	75.0–100.0	82.9	
	45–54 (d)	47.0	40.7–50.0	45.5		92.0	75.0–100.0	83.9	
	55–64 (e)	44.5	40.2–49.5	44.7		92.0	77.0–100.0	85.1	
	>65 (f)	43.0	42.0–48.0	45.1		75.0	75.0–100.0	81.0	
Marital status	Single	48.0	44.0–51.7	47.6	$p=0.268$** χ^2: 2.634	92.0	67.0–100.0	82.9	$p=0.890$** χ^2: 0.234
	Married	47.0	42.0–51.0	46.5		92.0	75.0–100.0	83.1	
	Spouse deceased/divorced	45.5	44.0–48.7	46.3		87.5	76.7–100.0	82.4	
Family type	Nuclear family (a)	47.0	43.0–51.0	46.8	$p=0.268$** χ^2: 2.637	92.0	75.0–100.0	82.6	**$p<0.001$**** χ^2: 15.519 $\eta^2_H=0.03$ c > a, b
	Extended family (b)	45.0	41.5–50.2	46.0		83.0	67.0–100.0	79.7	
	Living alone (c)	49.0	41.0–52.5	48.8		100	100.0–100.0	97.4	
Place where most of the life was spent	City	47.0	43.0–51.0	46.8	$p=0.289$** χ^2: 2.482	92.0	75.0–100.0	83.3	$p=0.430$** χ^2: 1.688
	Town	49.0	44.0–52.0	48.2		83.0	67.0–100.0	79.6	
	Village	46.0	44.2–49.0	44.8		92.0	69.0–98.0	83.5	
Income status	Income greater than expenses	46.0	43.0–51.0	46.6	$p=0.673$** χ^2: 0.791	92.0	75.0–100.0	83.3	$p=0.497$** χ^2: 1.400
	Income equal to expenses	47.0	43.0–51.0	47.1		92.0	75.0–100.0	84.0	
	Income less than expenses	47.0	43.0–51.0	46.6		91.0	70.0–100.0	80.4	
Educational level	Bachelor's degree	47.0	42.0–54.0	47.2	$p=0.929$** χ^2: 0.147	83.0	67.0–92.0	80.5	$p=0.296$** $\chi2$: 2.434
	Master's degree	47.0	43.0–51.0	47.1		92.0	67.0–100.0	81.5	
	Doctorate	47.0	43.0–51.0	46.7		92.0	75.0–100.0	83.4	

(Continues)

TABLE 3 | (Continued)

Variable	Group	AIL-S				HL-S			
		Med	Q1–Q3	$\bar{x}$	Test stats	Med	Q1–Q3	x	Test stats
Faculty (Workplace)	Faculty of Health Sciences/ Nursing/Medicine/Dentistry	47.0	43.0–50.0	46.3	$p = 0.125$** χ^2: 16.457	92.0	75.0–100.0	85.4	**$p = 0.028$**** χ^2: 21.533 $\eta^2_H = 0.02$ b, d, k < a d, k < c
	Faculty of Humanities and Social Sciences/Education/ Arts and Sciences	47.0	45.0–53.0	47.7		83.0	67.0–92.0	78.1	
	School (Health and Technical Vocations)	48.0	44.0–52.5	47.4		92.0	75.0–100.0	84.4	
	Faculty of Engineering/ Architecture	48.5	44.7–55.2	48.8		74.0	58.0–92.0	74.1	
	Vocational School (other)	48.0	43.0–54.5	49.0		92.0	67.0–100.0	85.0	
	Faculty of Law/Political Sciences/Economics and Administrative Sciences	46.0	41.5–52.5	45.5		83.0	75.0–100.0	84.5	
	Faculty of Islamic Studies/Theology	45.0	40.0–51.0	44.8		92.0	75.0–92.0	83.4	
	Faculty of Sport Sciences	48.0	44.0–53.0	48.2		92.0	75.0–100.0	88.0	
	Faculty of Fine Arts/ Conservatory	50.0	41.2–56.0	48.0		95.5	77.0–100.0	83.6	
	Agriculture/Forestry/ Veterinary/Fisheries	40.0	37.0–44.7	41.0		75.0	58.0–89.7	70.7	
	School of Foreign Languages	46.5	41.7–51.2	46.8		92.0	70.7–94.0	84.8	
	Other	47.0	42.0–50.0	46.5		83.0	79.0–100.0	84.8	
Academic title	Research assistant (a)	48.0	44.0–52.0	48.0	**$p < 0.001$**** χ^2: 25.149 $\eta^2_H = 0.04$ f < a, b, d, e g < a, b, d, e c, e < d	83.0	67.0–100.0	80.6	$p = 0.526$** χ^2: 5.137
	Research assistant (PhD) (b)	48.0	45.0–53.0	48.0		92.0	83.0–100.0	86.1	
	Lecturer (c)	46.5	42.7–51.0	46.8		92.0	67.0–100.0	81.4	
	Lecturer (PhD) (d)	51.0	46.0–55.0	50.6		92.0	83.0–100.0	86.4	
	Assistant professor (e)	47.0	43.0–51.0	46.7		92.0	75.0–100.0	85.0	
	Associate professor (f)	45.0	42.0–49.0	44.6		92.0	75.0–100.0	82.7	
	Professor (g)	45.0	42.0–48.0	44.9		83.0	69.0–100.0	79.5	

(Continues)

TABLE 3 | (Continued)

Variable	Group	AIL-S				HL-S			
		Med	Q1–Q3	$\bar{x}$	Test stats	Med	Q1–Q3	x	Test stats
Health status	Very good (a)	48.0	42.0–53.7	47.8	**$p=0.019$****	96.0	83.0–100.0	89.5	**$p=0.008$****
	Good (b)	47.0	44.0–51.0	47.2	χ^2: 10.003 $\eta^2_H=0.02$	92.0	75.0–100.0	83.8	χ^2: 11.717 $\eta^2_H=0.02$
	Moderate (c)	46.5	42.0–50.0	46.0	d < a, b, c	83.0	67.0–100.0	78.4	a > b, c, d, b > c
	Poor (d)	41.0	36.2–44.5	40.8		79.0	69.0–92.0	79.2	
Presence of disease requiring continuous follow-up/treatment	Yes	46.0	43.0–51.0	46.8	$p=0.727$* Z: −0.349	92.0	75.0–100.0	83.5	$p=0.745$* Z: −0.325
	No	47.0	43.0–51.0	46.9		92.0	75.0–100.0	82.8	
Skill level in using information technology tools	Moderate (a)	43.0	39.0–47.0	42.6	**$p<0.001$**** χ^2: 92.249 $\eta^2_H=0.21$ c > a, b b > a	92.0	75.0–100.0	82.9	$p=0.155$** χ^2: 3.730
	Good (b)	46.0	42.0–49.0	45.5		91.0	67.7–100.0	81.5	
	Very good (c)	52.0	47.5–56.0	51.1		92.0	75.0–100.0	85.8	
Daily internet use time	0–2 h	46.5	42.0–49.7	45.4	$p=0.080$** χ^2: 5.043	83.0	75.0–100.0	82.7	$p=0.467$** χ^2: 0.792
	3–4 h	46.0	42.0–50.0	46.2		92.0	75.0–100.0	82.6	
	5 h and above	48.0	43.0–52.0	47.5		92.0	75.0–100.0	83.3	
Using the AI applications	Yes	48.0	44.0–52.0	47.7	**$p<0.001$*** Z: −6.734 $r=0.33$	92.0	75.0–100.0	83.3	$p=0.717$* Z: −0.363
	No	41.0	36.0–45.0	40.2		92.0	67.0–100.0	81.3	
Finding AI applications useful	Yes	48.0	44.0–51.5	47.7	**$p<0.001$**** χ^2: 33.415 $\eta^2_H=0.07$ c < a, b	92.0	75.0–100.0	83.8	$p=0.131$** χ^2: 4.064
	No	47.0	44.5–48.5	46.5		67.0	34.5–100.0	65.1	
	Undecided	42.0	36.0–47.0	41.5		92.0	67.0–92.0	80.8	

Note: Effect size was calculated as Rank-Biserial Correlation (r) for the Mann–Whitney U-test and as ordinal Eta Squared (η^2_H) for the Kruskal–Wallis test.
Abbreviations: AIL-S, Artificial Intelligence Literacy Scale; HL-S, distribution of Health Literacy Scale; Med, median; p, significance; Q, quartile; $\bar{x}$, mean; Z, Z-table value; χ^2, Kruskal–Wallis H-Test (χ^2-table value).
*Mann Whitney U-Test.
**Kruskal–Wallis Test.

TABLE 4 | Regression analysis results for HL and AI-L.

	Health literacy					Artificial intelligence literacy				
Variables	***β***	**SE**	***t***	***p***	**VIF**	***β***	**SE**	***t***	***p***	**VIF**
Constant	85.055	12.684	6.706	< 0.001	—	42.273	3.828	11.044	< 0.001	—
Age group	3.734	1.628	2.294	**0.022**	3.295	−0.306	0.491	−0.623	0.534	3.295
Gender	−5.146	2.042	−2.520	**0.012**	1.133	0.015	0.616	0.024	0.981	1.133
Marital status	1.337	1.915	0.698	0.485	1.334	0.144	0.578	0.250	0.803	1.081
Family type	5.063	2.157	2.347	**0.019**	1.081	1.154	0.651	1.773	0.077	1.079
Place where most of the life was spent	−0.283	2.457	−0.115	0.908	1.079	0.346	0.741	0.466	0.641	2.172
Income status	−1.189	1.286	−0.924	0.356	1.051	0.197	0.388	0.508	0.612	1.051
Educational level	3.101	2.335	1.328	0.185	2.172	1.305	0.705	1.852	0.065	3.216
Faculty (workplace)	−0.371	0.263	−1.411	0.159	1.145	0.064	0.079	0.807	0.420	1.145
Academic title	−0.877	0.842	−1.041	0.298	3.216	−0.331	0.254	−1.303	0.193	2.728
Total years worked as an academician	−0.293	0.166	−1.772	0.077	2.728	0.007	0.050	0.149	0.882	2.728
Health status	−5.634	1.595	−3.533	**< 0.001**	1.174	−1.178	0.481	−2.447	**0.015**	1.174
Presence of disease requiring continuous follow-up/treatment	−1.766	2.186	−0.808	0.420	1.184	−0.734	0.660	−1.112	0.267	1.184
Skill level in using information technology tools	1.944	1.528	1.272	0.204	1.183	3.730	0.461	8.090	**< 0.001**	1.183
Daily internet use time	0.059	1.524	0.039	0.969	1.169	−0.099	0.460	−0.216	0.829	1.169
Use of AI applications	0.374	3.458	0.108	0.914	1.440	−4.978	1.044	−4.770	**< 0.001**	1.440
Finding AI applications useful	−2.417	1.587	−1.523	0.129	1.446	−1.124	0.479	−2.346	**0.020**	1.446
	Model statistics: $R^2 = 0.090$; Adjusted R^2: 0.054; $F(16, 400) = 2.477$; $p = 0.001$; RSE = 18.43					Model statistics: $R^2 = 0.319$; Adjusted R^2: 0.291; $F(16, 400) = 11.68$; $p < 0.001$; RSE = 5.563				

Abbreviations: *β*, regression coefficient; *p*, significance; SE, standard error; VIF, Variance Inflation Factor.

et al.'s (2025) review on HL educational approaches in higher education highlighted an absence of structured frameworks for academic staff and recommended development of profession-specific curriculum modules; institutional training programs for academicians are therefore important.

Many factors may influence HL. In this study, HL was higher among females, single-living individuals, those who rated their health as 'very good', and academicians working in health-related fields. The literature similarly reports higher HL among females (Republic of Türkiye Ministry of Health 2024; Sert et al. 2024; Dogan and Cetinkaya 2019) and among individuals with positive self-rated health (Sert et al. 2024; Dogan and Cetinkaya 2019). Although previous studies have suggested possible gender-related differences in health information-seeking behaviours (Dadipoor et al. 2018; Gokoglu 2021), the reasons underlying the higher HL scores observed among females in the present study cannot be established from these findings. Higher HL among those reporting good health may reflect greater personal responsibility for health decisions and stronger motivation to be healthy (Sert et al. 2024; Dogan and Cetinkaya 2019). Working in health fields may be associated with greater exposure to health-related information and knowledge; however, this difference should be interpreted in light of the small effect size observed.

The rapid spread of digital tools such as AI for searching and interpreting health information makes it strategically important for academicians to develop both HL and AI-L simultaneously. The increasing adoption of AI-based instructional and research applications in academia further underlines the importance of competence in this area (Zawacki-Richter et al. 2019). AI-L is considered a key avenue for academicians to build AI knowledge and skills (Drumm and Sami 2024). In this study, the mean AI-L score was 46.9 ± 6.6, within the score range of 12–60. As no validated cut-off or directly comparable normative reference was established for interpreting this score, it should be considered a descriptive measure

TABLE 5 | Correlation table between Health Literacy Scale (HL-S), Artificial Intelligence Literacy Scale (AIL-S), and AIL-S subdimension score.

	HL-S total score			
	Before the variables[a] are controlled		After the variables[a] are controlled[b]	
	p	*r*	*p*	*r*
AIL-S total score	$p < 0.001$	0.270	$p < 0.001$	0.232
AIL-S awareness subdimension	$p = 0.004$	0.141	$p = 0.016$	0.119
AIL-S usage subdimension	$p = 0.001$	0.159	$p = 0.002$	0.156
AIL-S appraisal subdimension	$p < 0.001$	0.204	$p < 0.001$	0.176
AIL-S ethic subdimension	$p < 0.001$	0.266	$p < 0.001$	0.242

Abbreviations: AIL-S, Artificial Intelligence Literacy Scale; HL-S, distribution of Health Literacy Scale; *p*, significance; *r*, correlation coefficient (Spearman's rho).
[a]Controlled variables: age, education, faculty, academic title, health status.
[b]The degrees of freedom (df) for all correlations are 410.

rather than classified as high or low. Although AI-L is a nascent concept (Almatrafi et al. 2024; Zhang et al. 2025), research remains limited. Osman et al. (2024) found that structured, module-based training and institutional advisory mechanisms significantly improved academicians' AI-L. Livberber and Ayvaz (2023) highlighted that Turkish academicians using ChatGPT require targeted guidance addressing both opportunities and ethical concerns. Recent studies have identified specific determinants of AI-L: Liu et al. (2025) showed that among academicians seeking health information via generative AI chatbots, digital literacy, cognitive trust, and user motivation were determinants of AI-L; Jin et al. (2025) reported that AI can reduce user trust. Accordingly, training that solely imparts basic AI knowledge may be insufficient; AI-L education should encompass correct usage strategies, trustworthiness management, and ethical appraisal skills (Omwanghe and Ogiamien 2025; Dringo-Horvath et al. 2025). This broader approach would enable academicians to maximize technological benefits while managing potential risks.

Academicians occupy a key position in supporting students' AI-L development (Drumm and Sami 2024). Understanding how demographic factors such as age, gender, teaching experience, and field of work are associated with AI-L is critical (Liu et al. 2025; Drumm and Sami 2024). In the present study, younger academicians (25–34 and 35–44) exhibited higher AI-L, whereas associate professors and full professors, those who rated their health as 'very poor,' those with only moderate IT skills, nonusers of AI applications, and those ambivalent about AI usefulness had lower mean AI-L scores. However, the differences observed for age and academic rank in the group comparisons should be interpreted cautiously, as these variables were not retained as statistically significant factors in the multiple regression model. In contrast, perceived health status, IT usage skills, AI application use, and perceived usefulness of AI applications remained significantly associated with AI-L after adjustment for other variables. Notably, IT usage skills showed a relatively large effect size, highlighting their relevance to AI-L. These results underscore the need for targeted interventions. Because AI is a contemporary phenomenon commonly used by younger 'digital native' cohorts (Liu et al. 2025), differences in exposure to and familiarity with emerging technologies may partly explain the age-related variations observed in this study. However, the cross-sectional design does not allow these differences to be attributed to age itself. Dringo-Horvath et al. (2025) demonstrated a positive relationship between digital competence and AI-L among academicians. The literature supports the present findings and emphasizes academicians' need for support and training to understand AI (Omwanghe and Ogiamien 2025; Drumm and Sami 2024). Enhancing AI-L requires tailored, demographically sensitive training and supportive environments (Dringo-Horvath et al. 2025). Universities can implement technology-literacy support services, create interdisciplinary AI-L programs, offer online and face-to-face workshops, host expert seminars, facilitate experience-sharing networks among academicians, analyse exemplar projects and case studies, and prepare guidance documents addressing ethics, data security, and AI integration (Ali and Richardson 2025; Dringo-Horvath et al. 2025; Drumm and Sami 2024).

The digital transformation in healthcare is altering not only how information is accessed but also how information is interpreted, appraised, and used reliably. This requires strengthening individuals' ability to correctly understand and apply health information and enhancing competencies to understand, appraise, and ethically use increasingly prevalent AI-based systems in health (AI-L) (Nutbeam 2023; Miao et al. 2025). This study found a positive association between HL and AI-L. The correlation was statistically significant but weak ($r = 0.270$), indicating that higher HL scores were associated with higher AI-L scores, although the strength of this relationship was limited. Positive but weak correlations were also observed between HL and all four AI-L subdimensions, with the strongest association found for the Ethics subdimension ($r = 0.266$). Importantly, the positive associations remained statistically significant after controlling for health status, age, education, academic title and faculty of employment. These findings suggest that HL and AI-L are related but distinct competencies, and that higher HL does not necessarily correspond to substantially higher AI-L. No prior studies were identified that directly examined this relationship. Osman et al. (2024) suggested that structured AI training modules could meaningfully improve not only technical skills but also health professionals' abilities to appraise and apply health information. Although these findings provide a rationale for considering both competencies in educational initiatives, the present study cannot establish whether improvements in one literacy domain lead to improvements in the other. From this perspective, interdisciplinary programs aiming to concurrently improve HL and AI-L may be effective. Considering AI tools' potential for searching, understanding, and appraising health information (Liu et al. 2025), addressing HL and AI-L together is relevant in the digital era for accurate interpretation of health data and reliable use of AI-supported

decision-support systems (Nejhaddadgar et al. 2023). Thus, universities could contribute to the simultaneous development of HL and AI-L through awareness initiatives, joint training programs, integrated curricula, scenario-based simulations and case-analysis workshops, gamified digital learning platforms, and augmented reality applications (Liu and Xiao 2021; Nutbeam 2023; Nejhaddadgar et al. 2023).

4.1 | Strengths and Limitations

To the best of our knowledge, this is the first study to examine HL and AI-L levels and their associated factors among academicians. However, several limitations should be acknowledged. The cross-sectional design prevents causal inferences, while voluntary online participation may have introduced selection bias. The response rate could not be calculated, limiting the assessment of potential non-response bias. The data were based on self-reported responses, which may have affected the accuracy of the findings. Additionally, unequal subgroup sizes and the overrepresentation of certain academic disciplines may limit the generalizability of the findings. Therefore, the findings should be interpreted cautiously and cannot be considered fully representative of all academicians in Türkiye.

5 | Conclusion

In this study, more than half of academicians demonstrated sufficient or excellent HL, whereas the mean AI-L score was 46.9 ± 6.6 within the range of the scale (12–60). Differences in HL were associated with gender, family type, perceived health, and field of work, while AI-L was associated with perceived health status, IT usage skills, AI application use, and perceived usefulness of AI applications in the adjusted analyses. A weak but statistically significant positive correlation was observed between HL and AI-L, indicating that these two literacy domains are related but distinct competencies. These findings highlight the relevance of considering both HL and AI-L in academic settings. Further research, particularly longitudinal and intervention studies, is needed to clarify the nature of the relationship between these competencies and to evaluate the effectiveness of educational approaches.

Author Contributions

Gülay Yazıcı: conceptualization, methodology, investigation, project administration, writing – review and editing, data curation. **Ayşegül Akca:** conceptualization, methodology, data curation, writing – original draft, writing – review and editing. **Erdal Ceylan:** conceptualization, formal analysis, writing – original draft, writing – review and editing, data curation. **Halil Tayyip Uysal:** data curation, writing – original draft, conceptualization. **Burçin Aysu:** data curation, writing – original draft, conceptualization.

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Generative AI statement: The authors declare that no Gen AI was used in the creation of this manuscript.

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Ethics Statement

This study was approved by the Ankara Yildirim Beyazit University Ethics Committee (22.05.2025, 05-1313). The goal of the study was explained to participants before they filled out the online form, and they were asked to tick the 'confirmation checkbox' to show their agreement.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data available on request due to privacy/ethical restrictions.

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