Attitudes of Hungarian Higher Education Students towards Consulting ChatGPT on Medical Topics: Links to eHealth Literacy and Technological Acceptance

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Abstract: Artificial intelligence (AI) tools such as ChatGPT are increasingly integrated into healthcare, offering new opportunities for health information access and literacy. This study investigated attitudes toward ChatGPT and AI in healthcare among Hungarian higher education students, focusing on the role of age, gender, education, and income. A cross-sectional online survey (N = 172) was conducted between November 2024 and May 2025, including the eHealth Literacy Scale (eHEALS), the Negative Attitudes toward Robots Scale (NARS), and two self-developed modules: an eight-item scale on attitudes toward AI in healthcare and a five-item scale on ChatGPT. Results showed that education and income were the strongest predictors of acceptance. Higher education and financial security were associated with greater digital health literacy, fewer negative attitudes, and more favorable views of ChatGPT. Gender and place of residence had minimal effects. Regression analyses revealed weak associations across most scales, except for a moderate link between the two custom measures. Findings highlight the importance of addressing educational, generational, and socioeconomic differences to foster equitable adoption and trust in AI-based healthcare tools.

Keywords: technological acceptance, ChatGPT, eHEALS, NARS, Hungarian students

1 Introduction

In contemporary society, rapid technological change, growing demands for efficiency, and the desire for instant solutions are driving digital transformation and increasing human–machine interactions across all domains. These interactions, ranging from robots to autonomous systems, offer unique advantages over traditional approaches and hold significant potential. While individuals generally recognize the convergence of technology and daily life, attitudes toward this shift remain mixed. Studies suggest that those with greater technological knowledge are more receptive to change and better able to appreciate its benefits [1–4].

Artificial intelligence (AI) is a rapidly evolving field of computer science encompassing systems capable of responding to environmental stimuli or data input, improving performance through iterative learning. This process relies on mathematical, programming, and statistical methods to detect and correct errors [5–7]. AI encompasses several domains, including machine learning, deep learning, and natural language processing (NLP). ChatGPT, developed by OpenAI and based on the GPT-3 model, is an NLP application trained on vast datasets of conversations to produce human-like responses [8].

In healthcare, ChatGPT's human-like dialogue capabilities can enhance public health literacy by providing information on topics such as preventive care, chronic disease management, vaccinations, and environmental health risks [10–13]. It offers accessible, on-demand health information, explains medical terminology, and guides users toward reliable sources. While valuable for education and preliminary self-assessment, ChatGPT should supplement—not replace—professional medical advice. Ethical concerns, particularly regarding data privacy, remain central [14]. Effective integration into healthcare requires careful implementation, monitoring, and collaboration between developers and medical professionals [13].

Research indicates gender differences in technology acceptance: men often report higher perceived usefulness, ease of use, and self-efficacy compared to women [16–19]. In healthcare contexts, women may express more reservations toward AI, underscoring the need for gender-sensitive implementation strategies [19]. Generational differences are also evident. Younger cohorts, having grown up with digital technologies, generally display greater familiarity and comfort with AI, while older generations may require adaptation and confidence-building [9, 15, 20-22].

Educational attainment further influences AI acceptance. Higher education is associated with greater exposure to technology, stronger critical thinking skills, and reduced technophobia, fostering a balanced view of AI's potential and limitations [23-25]. Consequently, understanding the interplay between age, gender, and education is essential for promoting equitable adoption of AI tools like ChatGPT in healthcare.

2 Methods

2.1 Data Collection

The cross-sectional online survey was conducted between November 2024 and May 2025. Data collection was voluntary and targeted a university student population, with the questionnaire distributed online. A total of 172 valid responses were obtained through Google Forms. The sampling was random and included active, clearly identified Hungarian students aged 18 years or older, all of whom had attained at least a secondary school diploma. Participation was fully anonymous, and all respondents provided informed consent prior to participation, acknowledging that their responses would be used exclusively for research purposes. Only fully completed surveys were included in the analysis. The survey was administered in Hungarian.

2.2 Survey Tools

The questionnaire comprised five modules: demographic variables, the eHealth Literacy Scale, the Negative Attitudes toward Robots Scale (NARS), and an eight-item set of questions assessing attitudes toward robots and artificial intelligence in the context of medical inquiries.

2.2.1 Demographic Variables

Demographic variables included gender, age, place of residence, employment/study status, relative income, and highest completed level of education, ongoing studies, university attended, and field of study (classified according to the Hungarian Academy of Sciences – MTA).

2.2.2 eHealth Literacy

The eHealth Literacy Scale (eHEALS), developed by Norman and Skinner [32], is an eight-item self-report measure assessing perceived skills in finding, evaluating, and applying electronic health information. It addresses functional, interactive, and critical aspects of digital health literacy and is widely used in public health and healthcare research. Each item is rated on a five-point Likert scale ("strongly disagree" to "strongly agree"), yielding a total score of 8–40, with higher scores indicating greater skill. Items 1–2 assess awareness, 3–4 searching, 6–7 appraisal, and 5 and 8 utilization of health information. The scale has a single-factor structure, good internal consistency, and modest test–retest reliability. Two additional items—usefulness and importance of the Internet for health information—are included but not scored. The Hungarian version of the questionnaire was developed and validated by Zrubka [35].

2.2.3 Negative Attitudes toward Robots Scale (NARS)

The Negative Attitudes toward Robots Scale (NARS), created by Nomura et al. [27], [33], is a validated psychometric instrument that measures emotional, cognitive, and behavioral responses toward robots. It consists of multiple subscales assessing negative attitudes toward interaction with robots, social influence of robots, and emotions in situations involving robots. NARS has been applied across various domains, including healthcare, to evaluate technology acceptance and trust in robotic systems. Scores between 14-70. As no validated Hungarian translation of the NARS is available, we used our own translation of the questionnaire for this study.

2.2.4 Eight-item set of questions assessing attitudes toward robots and Artificial Intelligence in health-related questions

Survey items were developed drawing on the NARS by Nomura et al. [26], [27] and the Unified Theory of Acceptance and Use of Technology (UTAUT) model by Venkatesh et al. [28], both widely used frameworks for examining attitudes toward emerging technologies. NARS captures emotional, cognitive, and behavioral responses to robots, whereas UTAUT identifies determinants of technology acceptance, including trust, perceived usefulness, and behavioral intention. Additional insights were informed by prior research on healthcare robot acceptance [29], social cognition related to technology [30], and trust in medical AI [31].
The statements in this module were adapted to the healthcare context, addressing willingness to interact with robots and AI on medical topics (Statements 1, 3, and 5), trust in human versus AI-based medical decision making (Statements 2 and 4), perceived discomfort and ethical considerations (Statements 3, 5, and 8), and perceptions of the increasing role and future dominance of AI and robotics in medicine (Statements 6–8). (Table 1)
Responses to each statement were recorded using a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). Scores between 8 and 40 in total.

Table 1

8-item self-developed questionnaire

Statement	**UTAUT Construct**	**NARS Subscale**	**Justification**
1. I would have no problem discussing medical issues with robots or artificial intelligence.	Effort Expectancy (EE)	S1 – Negative attitudes toward situations of interaction with robots	Indicates perceived ease and comfort in interacting with AI/robots in healthcare, suggesting low interaction-related anxiety.

2. I trust doctors more than robots or artificial intelligence.	Performance Expectancy (PE) / Trust	S2 – Negative attitudes toward the social influence of robots	Reflects comparative trust in human providers over AI, tied to perceived capability and social role.
3. I would feel nervous discussing my medical condition with a robot.	Effort Expectancy (EE)	S1 – Negative attitudes toward situations of interaction with robots	Captures emotional discomfort and anticipated difficulty in direct health-related interaction with robots.
4. I would not mind if robots or AI made decisions in medical matters.	Performance Expectancy (PE)	S2 – Negative attitudes toward the social influence of robots	Suggests acceptance of AI/robot decision making, indicating lower concern over their societal role in healthcare.
5. I would not mind showing a part of my body to a robot for medical examination purposes.	Effort Expectancy (EE)	S1 – Negative attitudes toward situations of interaction with robots	Reflects willingness to engage in physically intimate medical interactions with robots, indicating low perceived barriers.
6. I think medicine is already highly dependent on robots.	Social Influence (SI)	S2 – Negative attitudes toward the social influence of robots	Expresses perception of current technological integration in medicine, shaped by societal observation and norms.
7. I am not bothered by the increasing use of AI and robots in medicine.	Social Influence (SI) / Performance Expectancy (PE)	S2 – Negative attitudes toward the social influence of robots	Indicates acceptance of growing AI/robot adoption, influenced by societal attitudes and perceived benefits.
8. I feel that in the future robots and AI will dominate healthcare.	Facilitating Conditions (FC)	S2 – Negative attitudes toward the social influence of robots	Reflects expectation of future widespread integration, assuming infrastructure and societal readiness.

2.2.5 Artificial intelligence in the context of medical inquiries

The five-point Likert scale questionnaire also included a five-item set of self-developed questions specifically related to the use of ChatGPT in healthcare applications. These items were developed using the UTAUT model by Venkatesh et al. (2003), a well-established framework for explaining technology adoption behavior. UTAUT identifies four core determinants of user intention and technology use: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). The statements were designed to assess perceptions of ChatGPT in a healthcare context, focusing on trust, behavioral tendencies, health literacy, and expectations. Specifically, they examined trust in ChatGPT for health information (Statements 1 and 2), behavioral patterns in health information seeking (Statements 3 and 4), and expectations for future use (Statement 5) [25]. (Table 2)

Table 2

5-item self-developed questionnaire

Statement	**Mapped UTAUT Construct**	**Justification**
1. I consider ChatGPT to be a reliable source for questions about my medical and health conditions.	Performance Expectancy (PE)	Reflects the belief that ChatGPT effectively supports health-related tasks by providing reliable information.
2. In my opinion, the usage of ChatGPT has a positive impact on the health literacy of society.	Social Influence (SI)	Indicated the perceptions that ChatGPT benefits society at large, shaping attitudes through perceived collective usefulness
3. I ask health questions to ChatGPT more often than to a doctor.	Facilitating Conditions (FC)	Suggests that ChatGPT1s availability, convenience, and accessibility enable its frequent use over traditional consultation
4. I would rather go to ChatGPT with uncomfortable, overly personal questions than see a doctor in person.	Effort Expectancy (EE) (with elements of PE)	Shows comfort in using ChatGPT for sensitive topics, reducing effort and emotion barriers, while also implying trust in its usefulness
5. I believe that ChatGPT will soon be part of everyday healthcare.	Facilitating Conditions (FC)	Reflects expectations of future integration into healthcare systems, assuming supportive infrastructure and institutional adaptation.

2.3 Data Analysis

2.3.1 Descriptive Statistics

Descriptive statistics were used to summarize the dataset and examine variable distributions. Measures of central tendency (mean, median, mode) and dispersion (variance, standard deviation) were calculated to identify patterns, outliers, and the overall structure of the data. Analyses were performed in both Microsoft Excel and SPSS 16.0 to ensure consistency. Group differences were tested using Analysis of Variance (ANOVA), with significance set at $p < 0.05$. Significant results were followed by post hoc tests to identify specific between-group differences. Excel was used for its accessibility in preliminary calculations, while SPSS provided advanced statistical testing and post hoc procedures.

2.3.2 Linear Regression

Linear regression, conducted in Microsoft Excel, was used to evaluate the relationship between dependent (Y) and independent (X) variables. The coefficient of determination (R^2) was calculated to assess model fit, with higher values indicating stronger explanatory power.

3 Results

3.1 Survey Composition and Demographics

The sample comprised 55.8% females and 90.7% Generation Z, with 18–21-year-old's accounting for 51.7% of all respondents. Geographically, 32.6% resided in the capital. Regarding occupational status, 52.9% were students only, and 32.6% both studied and worked. One respondent reported regular household financial difficulties. In terms of financial capacity, 47.7% could save a small amount and 24.4% a substantial amount. Most respondents held a secondary school diploma (73.3%) and were enrolled in a bachelor's program (68%). (Table 3)

Table 3

Demographic variables

Sociodemographic variables		**Total sample**	
		N	**%**
Total sample		172	100.0
Gender	Male	76	44.2

	Female	96	55.8
Age	18-21 years (Gen Z)	89	51.7
	22 - 28 years (Gen Z)	67	39
	29 - 44 years (Millennials)	15	8.7
	45+ years (Gen X)	1	0.6
Place of residence	Capital city	56	32.6
	City with county rights	32	18.6
	Other town	46	26.7
	Other settlement	38	22.1
Employment/Study status	Employed*	22	12.8
	Student	91	52.9
	Both *	56	32.6
	Other**	3	1.7
Relative income	Regular financial difficulties	1	0.6
	Sometimes insufficient for basic needs	4	2.3
	Sufficient but unable to save	27	15.7
	Able to live on it with limited savings	82	47.7
	Very good financial situation with ability to save	42	24.4
	Prefer not to answer	16	9.3
Highest completed education	Primary school (max. 8 years)	4	2.3
	Vocational school	0	0
	Secondary vocational school	7	4.1
	High school diploma	126	73.3
	Higher education degree	35	20.3
Ongoing studies	Higher-level vocational training	34	19.8
	Bachelor's programme	117	68
	Master's programme	16	9.3
	Undivided programme (BA/BSc+MA/MSc)	1	0.6
	PhD	4	2.3

*Respondents employed at the time of the survey.

**Special circumstances e.i. childcare responsibilities

3.2 Descriptive statistics

3.2.1 Mean Scores and standard deviation

We compared digital health literacy (eHEALS), negative attitudes toward robots (NARS), and scores on two self-developed questionnaires: an 8-item scale on attitudes toward robots and AI in healthcare, and a 5-item scale on perceptions of ChatGPT in healthcare, across different social groups.

Differences between women (N = 96) and men (N = 76) were very small. Women had a mean eHEALS score of 29.08, while men scored 28.18. NARS was 43.01 for women and 41.12 for men. On the 8-item attitudes scale, women scored 21.66 and men 22.47. On the 5-item ChatGPT scale, women scored 11.86 and men 13.91. These results suggest that gender does not play an important role in how people see ChatGPT or robots in healthcare.

Age groups showed more variation. Younger adults aged 18–28 (N = 156) had an eHEALS mean of 28.42, while the 29–44 group (N = 15) scored higher at 31.07. Younger adults also had higher NARS scores (42.51) compared to 29–44-year-olds (39.07). On the 8-item scale, younger adults scored 21.93 versus 22.87 among 29–44-year-olds. On the 5-item ChatGPT scale, scores were 12.72 versus 13.40. This suggests that even though younger people have strong digital skills, they are less sure about the value of ChatGPT and AI in healthcare.

Respondents living in cities (N = 88) scored slightly higher than those in towns and villages (N = 84). City residents had a mean eHEALS score of 28.86 versus 28.50 in rural areas. NARS was 41.82 in cities and 42.55 in towns/villages. On the 8-item scale, city residents scored 22.27 compared to 21.75 in rural areas. On the 5-item ChatGPT scale, scores were 13.45 in cities and 12.05 in rural areas. These gaps were small.

The income was linked to attitudes. Respondents able to save money (N = 124) had higher digital literacy (eHEALS = 28.91) compared to those with financial difficulties (N = 5, eHEALS = 27.80) or those with only sufficient income but unable to save (N = 27, eHEALS = 26.96). Negative attitudes were lowest in the able-to-save group (NARS = 42.00) and highest among those with financial difficulties (NARS = 46.40). On the 8-item scale, the secure group scored 22.27 compared to 20.70–24.20 in the less secure groups. On the 5-item ChatGPT scale, the secure group scored 12.84 compared to 12.00–16.80 in less secure groups.

Education was an important factor. Respondents with a university degree (N = 35) had higher digital literacy (eHEALS = 30.74) compared to those with only a high school diploma (N = 137, eHEALS = 28.16). Negative attitudes were lower among university graduates (NARS = 39.17) compared to those with secondary education (42.94). On the 8-item scale, graduates scored 22.74 versus 21.83. On the 5-item ChatGPT scale, scores were 12.86 versus 12.74.

Students currently in higher-level programs (MA/MSc or above, N = 21) reported stronger digital skills (eHEALS = 31.24) and fewer negative attitudes (NARS = 38.95) than those studying at BA/BSc level (N = 151, eHEALS = 28.33; NARS =

42.62). On the 8-item scale, MA/MSc+ students scored 22.81 versus 21.91. On the 5-item ChatGPT scale, scores were 12.95 versus 12.74. (Table 4)

Overall, education and income had the strongest effect on attitudes. Gender and place of residence had little effect. Middle-aged, well-educated, and financially secure people were the most open to ChatGPT and AI in healthcare. Younger adults, despite their digital skills, were less sure of its value. Older adults saw its potential but were more cautious.

Table 4

Mean and Standard Deviations for the sub

		N	eHEALS		NARS		8-item		5-item	
			(Mean)	(SD)	(Mean)	(SD)	(Mean)	(SD)	(Mean)	(SD)
Gender	female	96	29.08	5.52	43.01	6.31	21.66	2.75	11.86	3.55
	male	76	28.18	5.37	41.12	7.85	22.47	3.78	13.91	4.15
Age	18-28	156	28.42	5.42	42.51	7.21	21.93	3.34	12.72	4.07
	29-44	15	31.07	5.48	39.07	4.67	22.87	2.36	13.4	2.59
Place of residence	Capital and other cities with county rights	88	28.86	5.57	41.82	6.87	22.27	3.38	13.45	4.04
	town. villages and others	84	28.5	5.37	42.55	7.31	21.75	3.13	12.05	3.73
Relative income	Able to save	124	28.91	5.28	42	6.93	22.27	3.15	12.84	3.86
	Financial difficulties	5	27.8	8.58	46.4	17.05	24.2	6.53	16.8	5.67
	Sufficient but unable to save	27	26.96	5.98	41.44	5.07	20.7	2.66	12	3.97
Highest	maximum	137	28.16	5.39	42.94	7.24	21.83	3.4	12.74	4.02

completed education	high school diploma									
	university degree	35	30.74	5.33	39.17	5.52	22.74	2.54	12.86	3.7
On-going studies	Min MA/ MSc	21	31.24	5.08	38.95	6.62	22.81	2.18	12.95	3.81
	max BA/ BSc	151	28.33	5.43	42.62	7.04	21.91	3.37	12.74	3.98

3.2.2 Statistical significance

Group comparisons revealed several significant differences. Education was a strong determinant: respondents with a university degree reported significantly higher digital health literacy ($p < .05$) and fewer negative attitudes toward robots ($p < .01$) than those with lower education. Gender differences were also observed for the 5-item ChatGPT scale ($p < .001$), with men and women differing in their responses. Place of residence was associated with the 5-item scale as well, with city residents scoring higher than those in towns and villages ($p < .05$). No statistically significant differences were found across age groups or income categories, although descriptive trends suggested lower scores among younger respondents and greater skepticism among older adults. (Table 5)

Table 5

Statistical significance

Grouping Variable	Measure	Test	p-value	Significant
Gender	eHEALS	t-test	0.28328918428138594	ns
	NARS		0.08964130604613854	ns
	8-item		0.11551325965372722	ns
	5-item		0.0008187514584277045	***
Age	eHEALS	ANOVA	0.12471367464042678	ns
	NARS		0.15171854938081228	ns
	8-item		0.5450052391618441	ns
	5-item		0.7393052643400501	ns
Place of residence	eHEALS	t-test	0.663413373676488	ns
	NARS		0.5012701431632323	ns

	8-item		0.2933483768141537	ns
	5-item		0.01880551524898276	*
Relative income	eHEALS	ANOVA	0.24743096690523156	ns
	NARS		0.45072078171036833	ns
	8-item		0.05076900110883547	ns
	5-item		0.08638576981171414	ns
Highest completed education	eHEALS	t-test	0.013630140374865124	*
	NARS	t-test	0.0012605532822863108	**
	8-item	t-test	0.08309520600997987	ns
	5-item		0.8750452231943592	ns
Ongoing studies	eHEALS	t-test	0.02176570023983231	*
	NARS		0.025781725024373293	*
	8-item		0.1096098339575436	ns
	5-item		0.815335460506183	ns

ns=not significant ($p \geq 0.05$)
*=significant at $p<0.05$
**=significant at $p<0.01$
***=significant at $p<0.001$

3.3 Linear Regression

Linear regression analyses were used to test the relationships between the scales (Table 6). The results showed only weak associations.
The relationship between eHEALS and NARS was negligible ($R^2 = 0.00003$), meaning that digital health literacy explained almost none of the variation in negative attitudes toward robots. The association between eHEALS and the 8-item attitudes scale was stronger, but still limited ($R^2 = 0.0528$), showing that digital literacy explained about 5.3% of the variation in attitudes toward robots and AI in healthcare. A similar result was found between eHEALS and the 5-item ChatGPT scale ($R^2 = 0.0676$), where digital literacy accounted for 6.7% of the variation.
Links with NARS were even weaker. The model predicting the 8-item attitudes scale from NARS explained only 1.2% of the variance ($R^2 = 0.0119$), while the model predicting the 5-item ChatGPT scale from NARS explained 2.2% ($R^2 = 0.022$).
The strongest relationship was observed between the 8-item attitudes scale and the 5-item ChatGPT scale, with an R^2 of 0.3008. This means that the 8-item scores explained about 30% of the variance in the 5-item scores, suggesting a moderate link between general attitudes toward AI/robots in healthcare and specific perceptions of ChatGPT.

Overall, most regression models showed very low explanatory power, except for the model connecting the two self-developed scales, which displayed a moderate association.

Table 6

Linear regression analyses

Variables	R^2
eHEALS* vs NARS*	3E-05
8-item questionnaire* vs eHEALS*	0.0528
8-item questionnaire* vs NARS*	0.0119
5-item questionnaire* vs eHEALS*	0.0676
5-item questionnaire* vs NARS*	0.022
5-item questionnaire* vs 8-item questionnaire*	0.3008

*Each respondent's score reflects the sum of points in the respective subsection of the questionnaire

4 Discussion

Our study showed that age, education, and income shape how people think about ChatGPT and AI in healthcare, while gender and place of residence play only a minor role.

One clear finding is that Millennials (29–44 years old) had higher digital health literacy (eHEALS) scores than Generation Z (18–28 years old). Several factors may explain this. Millennials are more likely to be parents, caregivers, or managing chronic conditions, which requires active searching for online health information. This repeated practice likely builds stronger skills in finding, judging, and applying health resources [35-36]. Generation Z, despite being "digital natives," often use the internet more for entertainment and quick social media consumption than for critical information seeking. This reliance on platforms such as TikTok or Instagram can expose them to misinformation, which may weaken confidence in their ability to judge health information and limit their eHealth literacy [37-38].

Education also played an important role. Respondents with university degrees, and especially those in postgraduate studies, had higher eHEALS scores than those with only secondary education. This finding supports earlier studies showing that higher education improves eHealth literacy [39-40]. Education likely strengthens general skills in reasoning and information use, but also increases confidence in evaluating and applying online health sources. This may make highly educated people more ready to use eHealth tools effectively.

In contrast, NARS scores (negative attitudes toward robots) showed no meaningful link with eHEALS. This suggests that being skilled at using online health information is not directly influenced by how people feel about robots. Digital health skills appear to depend more on education, life experience, and personal health needs than on general feelings toward automation. Future studies could still test whether certain aspects of NARS, such as attitudes about the social role of robots, are more closely tied to willingness to use AI in healthcare [27, 41].

The lack of strong relationships between eHEALS, NARS, and the two custom scales (8-item attitudes toward robots/AI in healthcare, 5-item perceptions of ChatGPT) suggests that these measures capture different constructs. eHEALS reflects digital health literacy, NARS reflects emotional and cognitive reactions to robots, and the two custom scales capture context-specific attitudes toward AI in medical decision making. Each of these areas is shaped by different influences, such as education and online search habits for eHEALS, cultural norms for NARS, and trust or ethical concerns for AI [28, 42]. In addition, the limited variation in our sample—mostly young, student respondents—may have reduced the chance of finding significant overlap.

Looking through the UTAUT framework, the results highlight the importance of performance expectancy (perceived usefulness) and effort expectancy (ease of use). Middle-aged and higher-educated groups rated ChatGPT more positively on both dimensions, suggesting they see greater value in it. Younger adults, even with strong digital skills, rated ChatGPT as less useful and less easy to use. This shows that digital skills alone do not ensure acceptance; what matters more is whether people believe the tool is relevant and helpful for their health needs [28, 43].

Social influence and facilitating conditions help explain why education and financial security matter. Respondents with higher education and stable income reported higher digital literacy, fewer negative attitudes, and more favorable views of ChatGPT. These groups are likely to have more exposure to technology, more chances to build digital competence, and better access to resources, which increase trust in new healthcare technologies needs [43-44].

Finally, older respondents scored highest on NARS, showing that skepticism toward AI and automation in medicine is the most visible among this group. Even when they see potential benefits, older adults may remain cautious due to concerns about safety, ethics, or loss of human contact needs [45]. Building trust and addressing these concerns will be important if ChatGPT and similar tools are to be accepted more widely.

These findings carry several practical implications. First, healthcare educators should develop programs to improve digital health literacy among younger adults, who may be skilled users of technology but less critical in judging online health information. Second, policy-makers and healthcare institutions should address the attitudinal barriers among older adults by promoting transparent, trustworthy, and human-centered AI applications. Third, developers of AI tools such as ChatGPT should consider that education and income are strong predictors of acceptance; designing accessible, easy-to-understand interfaces may help reduce gaps across socioeconomic groups. Finally, building public trust through regulation, medical endorsement, and clear communication will be essential for wider acceptance and safe use of ChatGPT in healthcare.

Conclusions

This study examined digital health literacy, attitudes toward robots, and perceptions of ChatGPT in healthcare across social groups. The findings show that education and income are the strongest predictors of acceptance, while gender and place of residence play only minor roles. Millennials and middle-aged adults displayed higher eHealth literacy than younger respondents, likely due to greater health-related responsibilities and experience with online resources. Higher education was consistently linked to stronger digital skills, fewer negative attitudes toward robots, and more positive views of ChatGPT.

Although general digital competence (eHEALS) and negative attitudes toward robots (NARS) were not strongly related to context-specific attitudes toward AI, the link between the two custom scales on attitudes to robots/AI and perceptions of ChatGPT was moderate, suggesting that general and specific views of AI are connected but distinct.

Overall, the results indicate that successful integration of ChatGPT in healthcare will depend less on gender or place of residence and more on addressing educational, generational, and socioeconomic differences. To foster trust and broad acceptance, efforts should focus on strengthening digital health literacy among younger adults, building confidence among older populations, and ensuring that AI tools are accessible and understandable across diverse educational backgrounds.

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