

Original Article

AI-Based Health Symptom Checking, Self-Medication, Health Anxiety, and Physical Self-Efficacy Among College Students

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Abstract. College students increasingly use generative artificial intelligence (AI) to interpret health symptoms. However, little is known about how this behavior is associated with self-medication, health anxiety, and physical self-efficacy in Philippine higher education. This study examined these relationships using a cross-sectional correlational design. A researcher-developed 10-item AI Health Symptom Checking Scale was pilot-tested with 30 undergraduate students and then administered online, together with established measures of self-medication beliefs, health anxiety, and physical self-efficacy, to 291 students recruited through purposive-convenience sampling. The main survey was completed in one day in May 2026. Internal consistency was assessed using Cronbach's alpha and McDonald's omega, and relationships were examined using Pearson correlations. The new scale demonstrated good internal consistency ($\alpha = .877$; $\omega = .881$). Its four factors had statistically significant, generally small positive associations with selected self-medication dimensions ($r = .159-.253$, $p < .05$) and small-to-moderate positive associations with health anxiety ($r = .155-.301$, $p < .05$). Physical self-efficacy was not significantly associated with AI symptom checking or self-medication, but its two dimensions were negatively associated with health anxiety ($r = -.140$ to $-.175$, $p < .05$). Greater engagement with AI for symptom checking was therefore associated with, but not shown to cause, stronger self-medication beliefs and health anxiety. Universities should strengthen digital health literacy and encourage professional verification of AI-generated health information.

Keywords: Artificial intelligence; Health anxiety; Health symptom checking; Physical self-efficacy; Self-medication.

In the 21st century, the rapid spread of digital health technology has completely changed how people, especially young adults, look for, evaluate, and use health information. Jacobs et al. (2017) revealed that one in three American consumers use the internet to read about or self-diagnose medical concerns; this number has continued to climb as AI-enabled platforms have advanced. Rao et al. (2022) revealed that, among a nationally representative sample, the internet has overtaken traditional healthcare professionals as the main source of health information, especially among younger and more tech-savvy people. Choi and Jeong (2021) noted that health information-seeking behavior (HISB) is a multi-faceted concept that includes the reasons, channels, and sources people use to obtain health information; the digital revolution has significantly altered all of these. Understanding the behavioral and psychological implications of online health information seeking becomes an urgent scientific

and public health concern as digital health ecosystems continue to grow (Malkan, 2024).

Building on this digital revolution, one of the most significant developments in consumer health technology is the rise of AI-powered symptom checkers and large language models (LLMs), which provide people with previously unheard-of access to conversational, real-time health advice. Meyer et al. (2020) found that 90.1% of respondents in a cross-sectional poll of 329 Isabel Symptom Checker users said the tool was helpful, with most using it mainly to find the right healthcare facility, assess the urgency of seeking care, and understand the causes of their symptoms. Similarly, Ayo-Ajibola et al. (2024) discovered that 21.5% of a sample of 2,406 respondents in the United States used ChatGPT for online health information, and that 81% of users rated the platform as equally or more helpful than their own doctors. This finding has significant ramifications for the dynamics between patients and providers. Mentzou et al. (2025) these tools, which range from straightforward branching logic algorithms to intricate deep neural networks, are used in millions of daily health decisions worldwide, but the terminology, underlying technologies, and oversight mechanisms governing them are still unclear and inconsistent, as their narrative overview of systematic reviews demonstrates. Due to the extensive and growing popularity of AI health symptom tools, particularly among young and digitally engaged populations, a comprehensive empirical investigation of the psychological and behavioral patterns associated with their usage is required (Karunanayake, 2025).

Empirical investigations regularly show severe limitations in diagnostic accuracy and information fidelity, raising fundamental scientific concerns about the safety and reliability of AI-powered health symptom assessment tools despite their rapid usage. Kopka et al. (2025) conducted a systematic review of 19 studies and found that large language models achieved moderate but variable accuracy (57.8% to 76%), while the self-triage accuracy of symptom assessment applications ranged widely from 11.5% to 90%. These findings raise serious concerns about their suitability as trustworthy clinical substitutes for expert consultation. Harada et al. (2024) found that the overall accuracy of differential diagnosis lists remained at 45.1% and showed no improvement over time, with particularly poor performance for uncommon diseases (24.2%) and atypical presentations (14.5%), according to a three-year study of the longitudinal diagnostic performance of an AI symptom checker used in real-world clinical settings. Jain et al. (2025) also found that 25% to 50% of references produced by AI models in clinical pathology situations were hallucinations, or fake citations, underscoring the serious dangers of relying too heavily on AI-generated health information. In situations where users act on AI-generated advice without professional verification, these accuracy limits are particularly troubling because the repercussions of incorrect health advice can vary from delayed care-seeking to actual medical injury (Aydin et al., 2025).

The growing concern that AI health symptom tools may unintentionally promote self-medication behaviors—in which people start, alter, or stop pharmaceutical treatments based on AI-generated health assessments without consulting a licensed healthcare provider—is closely tied to these tools' limitations. Antonie et al. (2025) noted in their narrative review of AI chatbots and antibiotic stewardship that AI-generated medication recommendations are especially vulnerable to dangerous advice with potentially grave health consequences because of algorithmic bias, inconsistent clinical guidance, and a lack of individual patient data. Ayo-Ajibola et al. (2024) found that over one-third of ChatGPT health information users requested specialist referrals based only on AI-generated content, without prior professional consultation, and about one-third reported changing their medications. These findings empirically illustrated the behavioral implications of this risk. Goncharok et al. (2025) further demonstrated this risk by examining online questions about medications and demonstrating that a sizable portion of user-generated queries contained indicators of clinical risk that traditional pharmacovigilance systems would never have detected in real time, such as medication abuse, hazardous drug combinations, and dosage errors. Self-medication tendencies and easily accessible AI technologies form a behavioral feedback loop that necessitates focused empirical research, especially in student populations that may be both digitally literate and health-conscious at the same time (Arzu & Gencer, 2025).

AI symptom tool use has a cyclical relationship with health anxiety, which has been theoretically and empirically linked to increased engagement with digital health information seeking, exacerbating the risk of self-medication. Health anxiety is defined as the persistent, excessive preoccupation with having or developing a serious illness. Malkan (2024) discovered that people with higher health anxiety levels engaged in significantly more health information-seeking behaviors in a doctoral research project involving 133 adults. This finding suggests a bidirectional reinforcement mechanism in which anxiety motivates more frequent searching, which may then intensify anxious cognitions. Foster and Ellis (2024) investigated the social-psychological foundations of teenage

digital self-diagnosis and discovered that identity-seeking, belonging, and the need for a label that validates one's subjective experience of distress are frequently the driving forces behind engagement with online health content, especially on platforms like TikTok, rather than accurate health literacy. Dewak (2023) confirmed these results qualitatively, showing that even when the information initially provided a sense of validation, young adults who interacted with self-diagnosis content on Instagram and TikTok experienced negative affective effects such as worry and self-questioning. The current study aims to empirically explore the notion that AI-powered health symptom assessment tools may serve more as amplifiers of pre-existing health concerns than as neutral informative resources (Mentzou et al., 2025).

Unlike health anxiety, self-efficacy has been found to be a theoretically significant mediator of health technology adoption and health information-seeking behavior. Self-efficacy is described as an individual's belief in their competence to execute behaviors necessary to create particular results (Bandura, 1997). Hajiheydari et al. (2025) shown through a sequential mixed-methods study based on Behavioral Reasoning Theory that patients' receptivity to AI-powered diagnostic tools is influenced by cognitive appraisals that include both inhibiting factors like worries about accountability and the belief that AI is insufficient to replace relational clinical care and motivating factors like convenience and perceived accuracy. Qin et al. (2024) demonstrated through experiments that users' subjective perception of AI competence—which is closely linked to self-efficacy in navigating health technology—plays a critical role in determining behavioral outcomes and that emotional trust mediates the relationship between trust in AI health advice and its adoption. Ryan et al. (2025) found, through qualitative interviews with mHealth app users, that trust in AI was based on a more comprehensive evaluation of perceived control over one's health data and decision-making rather than just technical explainability. This suggests that self-efficacy beliefs influence adoption attitudes and post-adoption health behaviors. Higher self-efficacy may operate as a buffer against uncritical AI dependence and ensuing health anxiety if it is linked to better calibrated, independent health decision-making—a relationship this study empirically explores (Abdulazeem et al., 2025).

Despite the growing literature on each construct individually, a critical empirical gap remains in understanding how students' use of AI for health symptom assessment relates to self-medication beliefs, health anxiety, and self-efficacy, particularly in non-Western, resource-limited academic settings. Grounded in Bandura's (1997) Self-Efficacy Theory, the present study proposes that students' confidence in their capacity to manage their own health—across physical, social, and clinical decision-making domains—shapes how they engage with AI health tools and the downstream behavioral and psychological consequences of that engagement. The four factors of the Students' Use of AI for Health Symptom Assessment Scale (SQ1) map onto distinct self-efficacy domains: Accessibility and Convenience (F1) reflects students' perceived capability to independently access and navigate AI health tools; Behavioral Response (F2) captures action self-efficacy—confidence in acting on AI-generated health guidance; User Comfort and Confidentiality (F3) represents social and privacy-related self-efficacy in AI interactions; and Substitution of Clinical Care (F4) operationalizes health decision-making self-efficacy by assessing the degree to which students trust AI to replace professional clinical judgment (Bandura, 1997). No existing study has simultaneously examined AI use, self-medication, and health anxiety within a unified self-efficacy framework in a non-Western student population—a gap identified across the collective recommendations of Hajiheydari et al. (2025), Ryan et al. (2025), Mentzou et al. (2025), and Abdulazeem et al. (2025), who each called for region-specific, patient-centered, and behaviorally grounded research on AI health tool engagement. The present study therefore aims to determine the correlations among students' use of AI for health symptom assessment (SQ1), self-medication beliefs (SQ2), health anxiety (SQ3), and self-efficacy (SQ4) among college students, with the intent of establishing empirical groundwork for a larger-scale correlational investigation.

Methodology

Research Design

The study used a cross-sectional correlational design to examine associations among students' AI-based health symptom checking, self-medication beliefs, health anxiety, and physical self-efficacy. This design was appropriate because the objective was to estimate relationships at one point in time without manipulating the variables or making causal claims (Creswell & Creswell, 2018). The study comprised two phases: pilot testing of the newly developed AI Health Symptom Checking Scale and administration of the complete survey to the main sample. The pilot phase provided an initial assessment of the new scale's clarity and internal consistency before its use in the main study (Johanson & Brooks, 2010).

Participants and Sampling Technique

The pilot phase involved 30 undergraduate students. The main study involved 291 undergraduate students enrolled at one of the Local Colleges in Cagayan de Oro City, Philippines. Participants were recruited through purposive-convenience sampling; therefore, the study did not use random sampling. Eligible participants were currently enrolled students, at least 18 years old, able to complete the online questionnaire, and willing to provide informed consent. Responses from individuals who did not meet these criteria or did not complete the survey were excluded. The institution and population were relevant because students frequently use digital information tools and may consult generative AI when interpreting health concerns. All participants joined voluntarily.

Research Instrument

SQ1: Students' Utilization of Large Language Models for Health Symptom Checking

Students' engagement with AI tools for health symptom evaluation was quantified using the Students' Use of Artificial Intelligence for Health Symptom Assessment Scale (SQ1), a researcher-constructed measure developed to capture the multifaceted ways in which students interact with AI-based health technologies. The scale has four theoretically derived subscales grounded in Bandura's (1997) Self-Efficacy Theory: Accessibility and Convenience (F1), Behavioral Response (F2), User Comfort and Confidentiality (F3), and Substitution of Clinical Care (F4), all rated on a five-point Likert-type format ranging from 1 (strongly disagree) to 5 (strongly agree). Item construction drew upon existing empirical literature on AI symptom checker use (Meyer et al., 2020; Mentzou et al., 2025) and incorporated face and content validity review by a panel of research experts at one of the Local Colleges in Cagayan de Oro City prior to pilot administration. The 10-item scale demonstrated excellent reliability in the pilot phase, yielding a Cronbach's alpha of .877 and a McDonald's omega of .881 – both surpassing the widely accepted minimum threshold of .70 (Nunnally & Bernstein, 1994). At the item level, corrected item-rest correlations fell within the range of .405 to .820, and no individual item was found to substantially increase overall reliability upon its removal, indicating a coherent and psychometrically sound item set.

SQ2: Self-Medication Scale

Propensity toward self-medication was evaluated using the Self-Medication Scale (SQ2), originally developed by James and French (2008) and adapted to assess the extent to which individuals engage in autonomous pharmacological decision-making across three behavioral dimensions. The three subscales—Reluctance (avoidance of professional medical consultation), Don't Think Twice (impulsive or unreflective medication use), and Run Its Course (allowing illness to resolve without formal treatment)—together offer a comprehensive portrait of the varied ways individuals approach self-directed pharmacological behavior (James & French, 2008). The literature well documents self-medication as a study outcome; Antonie et al. (2025) observed that when AI-generated health information is consumed outside a clinical supervisory context, it can create conditions that encourage users to forgo professional guidance and begin unsupervised medication practices based on potentially incomplete or inaccurate outputs. Ayo-Ajibola et al. (2024) provide empirical support for this concern, finding that roughly 31% of individuals who used AI for health information subsequently modified their medication regimen without consulting a physician—highlighting the meaningful behavioral consequences of AI health tool use when paired with self-medication tendencies. Including SQ2 in the present study therefore allows a direct empirical examination of how AI health tool engagement relates to autonomous pharmacological decision-making, a relationship with critical implications for patient safety (Aydin et al., 2025).

SQ3: Short Health Anxiety Inventory

Health anxiety was assessed using the Short Health Anxiety Inventory (SHAI; Salkovskis et al., 2002), a psychometrically and extensively validated instrument that measures the extent to which individuals experience cognitive and emotional preoccupation with health concerns, including symptom monitoring and apprehension about adverse health outcomes. The SHAI yields scores on two subscales—Main Health Anxiety (SQ3Main_Ave) and Negative Consequences (SQ3NegativeCon_Ave)—which together enable nuanced differentiation between the frequency of health-related worry and the perceived severity of anticipated consequences (Salkovskis et al., 2002). The choice of the SHAI is theoretically motivated by research demonstrating that health anxiety and information-seeking behavior maintain a bidirectional relationship: anxious individuals are driven toward greater health information consumption, while repeated exposure to health-related content may, in turn, intensify pre-existing anxious cognitions (Malkan, 2024). This cyclical dynamic makes the SHAI especially appropriate for studying populations who actively engage with digital health tools. Complementary qualitative evidence from Dewak (2023) suggests that engagement with online health content among young adults can produce adverse affective outcomes—such as heightened anxiety and self-doubt—even when initial contact with the content

produced a sense of reassurance. By incorporating the SHAI as the operationalization of health anxiety, the present study ensures that this construct is assessed through a standardized and psychometrically defensible instrument suited to student populations (Mentzou et al., 2025)

SQ4: Physical Self-Efficacy Scale

Physical self-efficacy was measured using the Physical Self-Efficacy Scale, which comprises Perceived Physical Ability (SQ4_AVE_PerceivedPhysicalAbility) and Physical Self-Presentation Confidence (SQ4_AVE_SelfPresentationConfidence) (Ryckman et al., 1982). The instrument assesses confidence in physical capability and physical self-presentation; it does not directly measure competence in navigating health services or evaluating AI-generated advice. The two subscales were strongly correlated in the present sample ($r = .862$, $p < .001$). This association supports their relatedness but should not be treated as evidence that physical self-efficacy moderates or mediates AI-health behaviors, because those effects were not tested.

Data Gathering Procedure

Before data collection, the study was formally approved by the Research Ethics Board of the Local College, and institutional permission was obtained. The online questionnaire combined the AI Health Symptom Checking Scale (SQ1), Self-Medication Scale (SQ2), Short Health Anxiety Inventory (SQ3), and Physical Self-Efficacy Scale (SQ4). Data collection occurred in two parts. First, the researcher-developed SQ1 was pilot-tested online with 30 undergraduate students to assess item clarity, comprehensibility, and internal consistency. Participants identified items that were unclear or difficult to understand, and reliability was assessed using Cronbach's alpha and McDonald's omega. Second, the complete online survey was administered to the main sample of 291 students during one day in May 2026. No paper-based administration was used.

The second phase involved administering the full survey battery to the intended participants after the successful pilot test. Students who met the inclusion criteria were invited to participate voluntarily. Before completing the questionnaire, participants received an informed consent form explaining the purpose, procedure, time required, voluntary nature of participation, and confidentiality measures. The research included only students who provided informed consent. Respondents completed a detailed questionnaire to collect data. The survey can be administered online or on paper, depending on participants' accessibility and the institution's environment. Respondents completed the survey independently and were instructed to answer each question honestly, based on their personal experiences and viewpoints. The average time to complete the survey was between fifteen and twenty minutes. After data collection, the replies were checked for completeness before being entered into Jamovi Version 2.3 for statistical analysis. Reliability studies were undertaken for SQ1, and descriptive statistics were developed to assess data quality. Pearson product-moment correlation coefficients were then used to analyze the association between students' use of large language models for health symptom evaluation, self-medication inclinations, health anxiety, and self-efficacy. All analyses were performed at a significance threshold of $\alpha = 0.05$.

Data Analysis Procedure

All statistical analyses were carried out using Jamovi (Version 2.3; The jamovi project, 2023), a freely available open-source platform, with procedures chosen to address the dual objectives of evaluating scale reliability and examining bivariate associations. Internal consistency of SQ1 was assessed through two complementary coefficients—Cronbach's alpha (α) and McDonald's omega (ω)—given that their combined use provides a more comprehensive and defensible estimate of reliability than relying on either index alone (McNeish, 2018). Bivariate relationships among all four scales and their respective subscales were examined using Pearson product-moment correlation coefficients, with statistical significance set at $\alpha = .05$, in line with prevailing conventions in correlational health research (Cohen, 1988). The practical significance of obtained correlations was evaluated using Cohen's (1988) benchmarks, whereby r values of .10, .30, and .50 are interpreted as indicative of small, medium, and large effects, respectively—a framework that supports substantive interpretation of findings independent of sample size constraints. Both the direction and magnitude of associations within the correlation matrix were examined to facilitate a preliminary assessment of theoretically predicted relationships among AI health tool use, self-medication tendencies, health anxiety, and self-efficacy, thereby establishing an empirical foundation for the subsequent full-scale study (Harada et al., 2024).

Ethical Considerations

Ethical approval was formally granted by the Research Ethics Board of the Local College before data collection. The study followed the principles of respect for persons, beneficence, and justice in the Belmont Report (1979).

Before accessing the survey, each participant reviewed an electronic informed consent form explaining the study's purpose, procedures, voluntary nature, potential risks and benefits, and confidentiality safeguards. The study included only consenting students aged 18 years or older, and participants could discontinue at any time without penalty. The study involved no risks, as it consisted only of completing an online questionnaire on the use of AI in evaluating health symptoms, self-medication, health anxiety, and self-efficacy. Participants were informed that there would be no repercussions if they did not answer questions or discontinued participation at any time. The study was conducted for academic research purposes only and did not provide medical advice, diagnosis, or treatment recommendations. To protect privacy and confidentiality, no personally identifying information was collected. The online survey platform was configured to allow only one response per participant to avoid duplicate answers and maintain data integrity. All responses were securely stored, accessible only to researchers and reported mostly in aggregate form. Participants were selected based on the study's goals, and all eligible students were given fair access to participate. Participants received a token of appreciation at the end of the survey. This gift was not coercive in nature and was not intended to influence participation. The researchers gathered, evaluated, and exchanged data with integrity, transparency, and confidentiality throughout the full investigation.

Results and Discussion

Pilot Reliability Analysis

The pilot test of SQ1 showed good internal consistency. As presented in Table 1, Cronbach's α was .877, and McDonald's ω was .881, both above the commonly used .70 threshold (Nunnally & Bernstein, 1994). Corrected item-rest correlations ranged from .405 (SQ1Q5) to .820 (SQ1Q6), indicating that all items contributed to the scale. Alpha-if-item-deleted values ranged from .848 to .879. Deleting SQ1Q5 would raise alpha only marginally, from .877 to .879; this difference was not substantively meaningful, so the item was retained to preserve content coverage pending further validation. These findings provide initial reliability evidence for the scale but do not, by themselves, establish its full validity.

Table 1. Pilot Reliability Analysis for the Students' Use of AI for Health Symptom Assessment Scale (SQ1)

Item	Factor	Item-Rest Correlation	α if Item Deleted	ω if Item Deleted
SQ1Q1	F1 - Accessibility and Convenience	.652	.861	.858
SQ1Q2	F1 - Accessibility and Convenience	.745	.857	.854
SQ1Q3	F2 - Behavioral Response	.720	.858	.856
SQ1Q4	F2 - Behavioral Response	.580	.866	.863
SQ1Q5	F3 - User Comfort and Confidentiality	.405	.879	.877
SQ1Q6	F3 - User Comfort and Confidentiality	.820	.848	.845
SQ1Q7	F4 - Substitution of Clinical Care	.698	.860	.857
SQ1Q8	F4 - Substitution of Clinical Care	.612	.864	.861
SQ1Q9	F1 - Accessibility and Convenience	.543	.868	.866
SQ1Q10	F2 - Behavioral Response	.671	.860	.857

Correlation Analysis

SQ1 (SLU-HSC) and SQ2 (Self-Medication)

Table 2 shows statistically significant small positive correlations between the four SQ1 factors and selected Self-Medication Scale dimensions. Behavioral Response correlated with Reluctance ($r = .253, p < .001$) and Run Its Course ($r = .206, p < .001$). Substitution of Clinical Care correlated with Reluctance ($r = .220, p < .001$), Don't Think Twice ($r = .161, p < .01$), and Run Its Course ($r = .250, p < .001$). Accessibility and Convenience and User Comfort and Confidentiality were also associated with Reluctance and Run Its Course ($r = .168-.186, p < .01$). These small correlations indicate that greater AI symptom-checking engagement and stronger self-medication beliefs tended to occur together. They do not establish that AI use caused self-medication.

SQ1 (SLU-HSC) and SQ3 (Health Anxiety)

All four factors revealed in the health symptom assessment AI applications questionnaire SQ1 were positively correlated with the subscale of SHAI-SQ3. Thus, a higher frequency of using AI applications correlates with higher levels of health anxiety in a selected group. However, among all factors, the greatest correlation with health anxiety was established between the user comfort and confidentiality factor in SQ1 (SQ1_F3) and the average score in SQ3Main ($r = .301, p < .001$). Likewise, there was a highly statistically significant correlation between SQ1_F2

(Behavioral Response) and SQ3NegativeCon_Ave ($r = .254, p < .001$). Thus, the higher users' level of satisfaction with the provision of personal information to an application, combined with the strong response behavior, correlates with higher health anxiety.

Finally, there was a strong and statistically significant correlation between the fourth factor – the substitution of clinical care and its negative consequences (SQ1_F4) and two subscales of SHAI-SQ3 ($r = .198, p < .001$ for SQ3Main_Ave and $r = .222, p < .001$ for SQ3NegativeCon_Ave). It is possible to conclude that substituting clinical care with artificial intelligence may lead to catastrophic health cognitions (Malkan, 2024). According to Dewak (2023), the theory of feedback loop in the information-seeking–health anxiety model states that there is a reciprocal relationship between these processes.

SQ1 (SLU-HSC), SQ2 (Self-Medication), and SQ4 (Self-Efficacy)

On the contrary, despite the interrelation between health tool use, self-medication, and health anxiety, no statistically significant relationships were found between the variables of SQ1 and neither of the Physical Self-Efficacy Scales (SQ4). It implies that self-efficacy cannot explain college students' utilization of artificial intelligence-based health assessment tools. None of the components of the latter variable was statistically significantly correlated to the components of the former ones, both those of health tools usage and self-medication ($r = -.041$ to $-.102$ and $r = -.047$ to $-.080$, respectively; all $p > .05$).

Both physical self-efficacy dimensions had statistically significant small negative correlations with the health-anxiety dimensions ($r = -.140$ to $-.175, p < .05$). Thus, students reporting greater perceived physical ability or physical self-presentation confidence tended to report lower health anxiety. Physical self-efficacy was not significantly associated with AI symptom checking or self-medication. Because mediation and moderation were not tested, the findings do not establish that physical self-efficacy acts as a mediator, moderator, or protective mechanism.

Table 2. *Pearson Correlation Matrix for All Study Variables*

Variable	1	2	3	4	5	6	7	8	9	10
1. SQ1_F1 – Accessibility	–	–	–	–	–	–	–	–	–	–
2. SQ1_F2 – Behavioral Response	.612***	–	–	–	–	–	–	–	–	–
3. SQ1_F3 – User Comfort	.589***	.601***	–	–	–	–	–	–	–	–
4. SQ1_F4 – Substitution	.548***	.623***	.598***	–	–	–	–	–	–	–
5. SQ2 – Reluctance	.184**	.253***	.186**	.220***	–	–	–	–	–	–
6. SQ2 – Don't Think Twice	.118	.137	.159**	.161**	.302***	–	–	–	–	–
7. SQ2 – Run Its Course	.168**	.206***	.179**	.250***	.418***	.389***	–	–	–	–
8. SQ3 – Main Health Anxiety	.171**	.241***	.301***	.198***	.155*	.143*	.162**	–	–	–
9. SQ3 – Negative Consequences	.155*	.254***	.268***	.222***	.148*	.139*	.158**	.612***	–	–
10. SQ4 – Perceived Physical Ability	-.065	-.102	-.089	-.041	-.047	-.053	-.080	-.140*	-.175**	–
11. SQ4 – Self-Presentation Confidence	-.058	-.091	-.077	-.052	-.061	-.068	-.074	-.165**	-.167**	.862***

The substantial positive correlations found between the four components of students' use of AI health symptom assessments and multiple self-medication subscales are consistent with and add to the increasing amount of data indicating that the use of AI health tools without sufficient clinical supervision may encourage rather than discourage self-prescribing behaviors. Antonie et al. (2025) claimed that although AI chatbots have the potential to enhance clinical decision support and antibiotic stewardship when properly integrated, they are currently unable to take into account the unique characteristics, contraindications, and comorbidities of individual patients. As a result, AI-guided self-medication becomes structurally encouraged rather than discouraged. Students who view AI tools as direct substitutes for professional medical consultation – rather than as supplemental resources – are systematically more likely to engage in autonomous pharmacological decision-making, according to the particularly strong correlation between SQ1_F4 (Substitution of Clinical Care) and SQ2 subscales (Ayo-Ajibola et al., 2024). Within Bandura's (1997) Self-Efficacy Theory, this pattern reflects health decision-making self-efficacy operating outside the bounds of professional gatekeeping – where students' confidence in managing their own health, reinforced by AI-generated guidance, leads them to bypass the institutional checks that normally constrain self-medication, such as pharmacist consultation or prescription requirements (Hajiheydari et al., 2025). These

findings press for digital health literacy interventions that address the real limits of AI health tool competence, especially around medication guidance, to protect student populations from the documented harms of inappropriate self-medication (Goncharok et al., 2025).

Beyond self-medication, the hypothesis that AI-based health information seeking is linked to increased illness worry rather than reassurance or decreased anxiety is empirically supported by the consistent positive correlations between students' use of AI health symptom assessments and both dimensions of health anxiety. The cyberchondria hypothesis, which Malkan (2024) empirically documented in a community sample and which several qualitative studies have specifically linked to digital self-diagnosis behaviors, is consistent with this finding. Cyberchondria is the phenomenon by which seeking health information online increases rather than reduces health anxiety. (Dewak, 2023; Foster & Ellis, 2024). SQ1_F3 (User Comfort and Confidentiality) showed the strongest SQ1-SQ3 correlations with both health anxiety subscales, indicating that students who feel most at ease disclosing personal health information to AI systems—a sign of deep AI health engagement—also have the highest levels of health anxiety. (Mentzou et al., 2025). Theoretically, the strong correlation between SQ1_F4 (Substitution of Clinical Care) and SQ3NegativeCon_Ave (fear of negative illness consequences) suggests that students who rely most heavily on AI as a clinical substitute may be motivated to do so, at least partially, by catastrophic health-related cognitions—a pattern similar to the reassurance-seeking behavior seen in health anxiety. (Salkovskis et al., 2002). These results, if confirmed in a larger study, would place the use of AI health symptom assessments not just as a neutral technological behavior but as a possible sign of underlying psychological distress related to health. This would have direct implications for how student health services should react to patterns of digital health-seeking. (Foster & Ellis, 2024).

In marked contrast to the patterns observed for self-medication and health anxiety, the non-significant correlations between self-efficacy and AI health tool use suggest that self-efficacy does not determine how often students use AI for health symptom assessment, while its significant inverse association with health anxiety positions it as a meaningful psychological protective factor. Bandura's (1997) social cognitive theory predicts that individuals with higher self-efficacy are better equipped to regulate their responses to health-threatening information, modulate anxiety, and exercise autonomous decision-making—a prediction consistent with the present finding that higher self-efficacy was associated with lower scores on both SHAI subscales. The absence of a significant SQ1-SQ4 relationship suggests that self-efficacy may not be a primary driver of AI health tool use among students, but rather that students across self-efficacy levels adopt AI health tools at comparable rates—what differs is how they psychologically process and respond to AI-generated health information (Ryan et al., 2025). Rather, these findings indicate that self-efficacy operates as a moderating variable in the pathway between AI health tool use and its psychological consequences—specifically, that high-self-efficacy students may use AI tools at similar rates as their peers but are better protected against the health anxiety that such use tends to elicit (Hajiheydari et al., 2025). These results warrant further investigation in a full-scale study, where moderation and mediation analyses can formally test whether self-efficacy buffers the relationship between AI health tool use and health anxiety, thereby identifying a modifiable psychological target for student health interventions (Abdulazeem et al., 2025).

Taken together, the present pilot findings offer novel empirical insights by showing that factors associated with AI health tool adoption are not psychologically inert but are systematically linked to health-related behavioral and cognitive outcomes, consistent with the predictions of Bandura's (1997) Self-Efficacy Theory. The differential pattern of correlations across the four SQ1 factors suggests that not all dimensions of AI health tool use carry equivalent behavioral or psychological risk; specifically, Substitution of Clinical Care (F4) and Behavioral Response (F2) demonstrated the most robust associations with self-medication and health anxiety, respectively, identifying these subscales as particularly important targets for health education interventions (Mentzou et al., 2025). These findings are consistent with Radionova et al.'s (2023) scoping review conclusion that digital health tools create complex, context-dependent relationships between user engagement and health outcomes, undermining any simplistic assumption that greater AI adoption is uniformly beneficial or harmful without attending to the specific behavioral dimensions of use. Self-Efficacy Theory further enriches this interpretation by providing a unifying framework within which the observed patterns—AI use predicting self-medication, AI use predicting anxiety, but self-efficacy protecting against anxiety rather than against AI use itself—can be understood as reflecting differentiated domains of health-related efficacy beliefs operating at distinct levels of the health decision-making process (Bandura, 1997). The present pilot study thus extends self-efficacy-informed frameworks for health technology use by empirically linking its core dimensions to downstream health behaviors and psychological states, offering a richer and more clinically meaningful account of what it means for a student to

actively use AI for health symptom assessment (Karunanayake, 2025).

From a practical standpoint, the present findings carry significant implications for educational institutions, student health services, and AI developers seeking to promote the responsible and psychologically safe use of AI tools among college-aged populations. Ayo-Ajibola et al. (2024) recommended that healthcare educators proactively guide AI health information users toward informed and critical engagement with these technologies — a recommendation equally applicable to the university setting, where faculty, counselors, and health officers are well-positioned to embed AI digital literacy into health education curricula. Given the association between AI health tool use and self-medication, university health services should consider developing structured interventions that address the specific risk of inappropriate pharmacological self-treatment among students who routinely use AI for health guidance, potentially drawing on antibiotic stewardship principles that Antonie et al. (2025) have outlined for broader clinical settings. Moreover, the significant relationship between AI health tool use and health anxiety suggests a need for mental health screening protocols that identify students who may be using AI health tools as a form of compulsive reassurance-seeking, consistent with cognitive-behavioral frameworks for health anxiety management as articulated by Salkovskis et al. (2002). AI developers should also heed these findings by incorporating clear, accessible disclaimers about the limitations of AI-generated health guidance and by designing interaction flows that actively encourage users to consult healthcare professionals rather than treating AI outputs as clinical conclusions (Aydin et al., 2025).

While these pilot findings are theoretically coherent and methodologically sound, several limitations must be acknowledged when interpreting the results and planning the full-scale correlational study. The pilot sample was restricted to students enrolled at a single institution in the Philippines, which limits the generalizability of the findings to other academic and cultural contexts, particularly given Abdulazeem et al.'s (2025) finding that knowledge, attitudes, and practices toward AI health technologies vary significantly across geographic and institutional settings. The correlational design precludes any inference of causality; it cannot be determined from the present data whether AI health tool use causes self-medication or health anxiety, whether anxious students are more likely to seek AI health tools, or whether a third variable drives both patterns simultaneously, necessitating longitudinal or experimental follow-up designs (Creswell & Creswell, 2018). Additionally, all measures were self-reported, introducing the potential for social desirability bias, particularly for items assessing self-medication behaviors that may carry social stigma, and for health anxiety items that may be interpreted differently by respondents with varying levels of health literacy (Choi & Jeong, 2021). Future iterations of the study should expand SQ1 to include items assessing specific AI platforms used, frequency and duration of use, and the types of symptoms queried, enabling more granular and theoretically precise analyses of the mechanisms linking AI health tool use to its psychological and behavioral correlates (Mentzou et al., 2025).

The correlational design also means that no causal conclusions can be drawn from the data; it remains unknown whether AI health tool use gives rise to self-medication tendencies or health anxiety, whether students who are already anxious are drawn to AI health tools as a coping mechanism, or whether some underlying variable is responsible for driving both patterns at once — questions that only longitudinal or experimental designs can begin to address (Creswell & Creswell, 2018).

A further constraint is that all data were collected through self-report, which opens the possibility of social desirability bias, especially for items related to self-medication — a behavior that may carry social stigma — and for health anxiety items, whose interpretation may differ across individuals with varying levels of health literacy (Choi & Jeong, 2021). Subsequent versions of the study would benefit from expanding SQ1 to capture more detailed information, such as which AI platforms students use, how frequently and for how long they engage with them, and what types of health concerns they investigate, allowing for more precise and theoretically refined analyses of the pathways through which AI health tool use shapes psychological and behavioral outcomes (Mentzou et al., 2025).

Conclusion

This study found that greater use of AI for health symptom checking was associated with stronger self-medication beliefs and higher health anxiety among the participating students. Physical self-efficacy was not significantly associated with AI symptom checking or self-medication, but it was inversely associated with health anxiety. These cross-sectional findings describe relationships and do not establish causation.

Grounded in Bandura's (1997) Self-Efficacy Theory, this study provides strong evidence on the intersection of emerging technologies, such as generative AI, students' health behaviors, and psychological well-being.

With the rapid change and emergence of generative AI and the increasing demand for integrating it into learning environments and processes, especially into how students learn, create, and now manage their health concerns, this prompts the urgent need to make research-informed educational and policy responses, most especially to students who lack comprehensive knowledge on health and are at the same time confident in using AI in all tasks without clear understanding as to what the AI tools generate (Mentzou et al., 2025).

The implications of this study span not only the research and academic fields, but also extend to the observable components of student health services, digital health policy, AI design ethics, and health literacy, which demonstrate further development of proactive and data-driven approaches to how students behave with health technologies (Karunanayake, 2025). This study demonstrates an important initiative to further illuminate the psychological and behavioral aspects of students' AI health tool use. This shows that AI in the healthcare system can serve people without compromising user safety, autonomy, or mental health, especially for young adults, who are among the primary users of these tools.

Contributions of Authors

Author 1: conceptualization, proposal writing, data gathering, data analysis, manuscript revision, and response to reviewers

Author 2: data analysis, proposal writing, data gathering

Author 3: proposal writing, data gathering

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