

# Domain-Specific Cyberchondria and AI-Assisted Health Information Seeking among Pre-Clinical Medical Students in South India: A Two-Wave Longitudinal Study

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## DOI:

10.55489/njmr.160420261370

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**Date of Submission:** 04/05/2026

**Date of Acceptance:** 11/07/2026

**Date of Publication:** 01/10/2026

## Funding Support:

None Declared

## Conflict of Interest:

The authors have declared that no conflict of interest exists.

## How to cite this article:

Rao MJ, Sridhar D, Kiranmai B. Domain-Specific Cyberchondria and AI-Assisted Health Information Seeking among Pre-Clinical Medical Students in South India: A Two-Wave Longitudinal Study. Natl J Med Res 2026;16(04):212-217. DOI: 10.55489/njmr.160420261370

## ABSTRACT

**Background:** Generative AI is widely used for health information seeking, but its longitudinal relationship with specific cyberchondria domains has not been examined. The objective was to examine domain-specific associations between AI-assisted health information seeking and cyberchondria among medical students, and to assess within-person change after AI adoption or discontinuation.

**Methods:** Prospective two-wave study of 100 pre-clinical MBBS students at a single South Indian government medical college (January-April 2026; 100% retention). The Cyberchondria Severity Scale (CSS-15) was administered at both waves. Students were classified by AI-use status across waves into persistent non-users, new adopters, discontinued users and persistent users. Cohen's d effect sizes, paired t-tests and Spearman rank correlations were applied.

**Results:** AI use was reported by 81% at Wave 1 and 83% at Wave 2. AI users scored higher than non-users on Excessiveness (d=0.96), Distress (d=0.55) and Reassurance (d=0.53); Compulsion and Mistrust differed minimally. In a small, underpowered subgroup of new adopters (n=12), Distress increased significantly ( $\Delta=+0.39$ , d=0.69, p=0.036); this within-person result is exploratory. Search frequency correlated with Excessiveness (p=0.47), Reassurance (p=0.57), Compulsion (p=0.35) and Distress (p=0.32). Pre-consultation symptom searching had a large effect on Excessiveness (d=1.04).

**Conclusion:** AI users showed higher Excessiveness, Distress and Reassurance; only Distress rose significantly, and only within a small new-adopter subgroup, where it should be read as exploratory. Search frequency was the most consistent and most modifiable correlate.

**Keywords:** Artificial intelligence, Cyberchondria, Health anxiety, Students, Medical, Longitudinal studies, Information seeking behavior, Help-seeking behavior

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**Publisher:** Medsci Publications [www.medscipublications.com]

ISSN: 2249 4995

Official website: www.njmr.in

## INTRODUCTION

Generative AI tools such as ChatGPT, Gemini and Claude are now widely used to look up health information. They differ from conventional search in an important way: a search engine returns a list of links and stops there, while AI assistants reply conversationally, answer follow-up questions and keep the user in dialogue. This conversational format is potentially relevant to cyberchondria - a pattern of repeated or compulsive searching for health information online that can heighten anxiety about one's health.[1,2] The repetitive searching, distress and reassurance-seeking that characterise the disorder [3] may be sustained more readily by a tool built to keep a conversation going than by a static page of links [4,5].

Despite this, AI-assisted health information seeking has not been studied as a distinct exposure in relation to the specific domains of cyberchondria. Most existing research treats all online health searching as a single behaviour and uses a single total CSS score, which collapses five distinct psychological processes into one number.[6,7] Each of the five domains captures something different: Excessiveness (searching the same symptoms repeatedly), Distress (feeling anxious after searching), Compulsion (searching interfering with daily activities), Reassurance (seeking confirmation of online findings from a doctor) and Mistrust (doubting the doctor's diagnosis). Whether these domains behave differently in students who use AI than in those who do not, or within the same students before and after they take it up, has not been investigated.

Pre-clinical MBBS students are a useful population for this question for two reasons. They have enough medical knowledge to read into symptoms but lack the clinical experience to contextualise them without anxiety, which makes them particularly susceptible to cyberchondria. They are also among the heaviest users of AI tools for academic and personal information.[8,9] A longitudinal design lets us look beyond cross-sectional comparisons and ask whether students who start or stop using AI show domain-level changes consistent with that shift.

The study had three aims. First, to quantify the association between AI-assisted health information seeking and each CSS-15 domain using effect sizes. Second, to test whether students who started or stopped using AI between the two waves showed corresponding within-person changes in their domain scores. Third, to characterise the dose-response relationship between overall search frequency and cyberchondria. To our knowledge, this is the first longitudinal, domain-level, AI-specific examination of cyberchondria among medical students.

## MATERIALS AND METHODS

**Study Design, Setting and Participants:** A prospective two-wave longitudinal study was conducted among pre-clinical MBBS students at a government medical college

in South India. Data were collected in January 2026 (Wave 1) and April 2026 (Wave 2), three months apart. The study was approved by the Institutional Ethics Committee of Government Medical College, Maheshwaram, Telangana, vide approval number IEC/GMC/MAHRM/2026/01. The approval covered the full longitudinal follow-up period including both waves of data collection. Electronic informed consent was obtained at both waves. All enrolled first- and second-year MBBS students were invited. Participants were matched across waves by year of study and roll number. Those with incomplete, duplicate, or unmatched responses, or who reported a pre-existing psychiatric diagnosis, were excluded. All 100 matched participants (50 first-year, 50 second-year) completed Wave 2, giving 100% retention. The college admits 50 MBBS students per year, so the first- and second-year pre-clinical cohorts together comprised 100 students (50 per year), all of whom were invited. Complete and matched responses at both waves were obtained from all 100 students (50 first-year, 50 second-year), giving a 100% response rate and 100% retention; the pre-specified exclusion criteria (incomplete, duplicate or unmatched responses, or a pre-existing psychiatric diagnosis) were applied but no eligible student required exclusion.

**Sample Size Estimation:** The a priori calculation assumed a repeated-measures comparison of AI users versus non-users - the two groups - across the two waves: detecting a small effect (Cohen's  $f = 0.10$ ) at  $\alpha = 0.05$  with 80% power required a minimum of 80 participants, which the matched sample of 100 satisfied for the primary user-versus-non-user analyses. The four-way AI-use transition classification (persistent non-users, new adopters, discontinued users, persistent users) was a secondary, exploratory stratification; the resulting new-adopter ( $n=12$ ) and discontinued-user ( $n=10$ ) subgroups fall well below this minimum and are underpowered, so their within-person results are treated as hypothesis-generating.

**Measurement Instrument:** The 15-item Cyberchondria Severity Scale (CSS-15) [10], a validated short form derived from the 33-item original [6], was used to assess cyberchondria. The 15-item version was chosen in preference to the more recent 12-item CSS (CSS-12) [11] because it retains the Mistrust subscale, allowing physician-trust beliefs to be examined as a distinct domain; the CSS-12 omits Mistrust owing to its weaker factor loading, and using it would have precluded the domain-level Mistrust findings reported here. Each item is rated 0 (Never) to 4 (Always); items 5, 12 and 15 are reverse-scored. Each of the five domain scores was calculated as the mean of its component items (range 0-4): Excessiveness (items 1, 2, 13), Distress (items 6, 9, 14), Compulsion (items 3, 4, 7), Reassurance-seeking (items 8, 10, 11) and Mistrust of medical professionals (items 5R, 12R, 15R). Cronbach's alpha indicated acceptable internal consistency at each wave (0.755 at Wave 1 and 0.812 at Wave 2).

**Exposure and Covariate Assessment: Primary exposure.** The primary exposure, AI-assisted health information seeking, was defined as any use of AI applications such as ChatGPT or Gemini to obtain health-related information, and was recorded as Yes/No at each wave. Students were assigned to one of four transition groups based on their AI-use status across both waves: persistent non-users (No→No), new adopters (No→Yes), discontinued users (Yes→No) and persistent users (Yes→Yes).

**Additional digital sources.** Google, YouTube, medical websites and social media were assessed at each wave. Search frequency (Rarely / Sometimes / Often / Always) and whether students searched symptoms before consulting a doctor (Yes/No) were recorded as behavioural covariates. Demographic variables included year of study, gender, residence, family income and education.

**Statistical Analysis:** Descriptive statistics summarised domain scores and source use at each wave. Change in source use across waves was tested by McNemar's test (continuity-corrected). To compare AI users with non-users on domain scores, Cohen's d was computed across the 200 wave-level observations. Because the same students contributed data at both waves, these pooled observations are not independent; Cohen's d values are therefore reported as descriptive effect-size summaries only, with no inferential p-values. All CSS scores are reported as mean item scores (range 0-4); the conventional summed score can be obtained by multiplying by 15.

Within-person changes between waves were assessed using paired t-tests within each transition group, with Cohen's d as the effect size. The No→Yes group assessed changes following AI adoption, while the Yes→No group assessed reciprocal changes following AI discontinuation. Dose-response was evaluated using Spearman correlation between search frequency and Wave 1 domain scores and by comparing mean domain scores across four frequency categories. All tests were two-sided with  $\alpha = 0.05$ . No formal correction for multiple comparisons was applied despite examining five domains across multiple transition groups; this was decided a priori, with findings interpreted collectively as patterns rather than individually confirmatory tests.

## RESULTS

The cohort comprised 100 MBBS students (50 first-year, 50 second-year; 67 female). AI use for health information seeking was reported by 81% at Wave 1 and 83% at Wave 2, with no significant change between waves (McNemar  $\chi^2 = 0.045$ ,  $p = 0.831$ ). Google was the most commonly used co-source (86% Wave 1, 79% Wave 2). Seventy-five percent of students searched symptoms before consulting a doctor at Wave 1. Most students were persistent AI users (71%); 12% newly adopted AI use, 10% discontinued it and 7% never used AI at either wave (Table 1).

**Table 1: AI-Use Transition Groups Across Waves (N = 100)**

| Transition Group     | Pattern | Cases (%) |
|----------------------|---------|-----------|
| Persistent non-users | No→No   | 7 (7)     |
| New adopters         | No→Yes  | 12 (12)   |
| Discontinued users   | Yes→No  | 10 (10)   |
| Persistent users     | Yes→Yes | 71 (71)   |

Note: McNemar's test (continuity-corrected) for AI-use changes across waves:  $\chi^2 = 0.045$ ,  $p = 0.831$ .

**Table 2: CSS-15 Domain Scores Across Waves (N = 100)**

| Domain                     | Wave 1<br>Mean±SD | Wave 2<br>Mean±SD | Change<br>(Δ) | Paired<br>p |
|----------------------------|-------------------|-------------------|---------------|-------------|
| Excessiveness              | 1.79±0.94         | 1.73±0.92         | -0.06         | 0.551       |
| Distress                   | 0.92±0.89         | 1.01±0.85         | +0.09         | 0.255       |
| Compulsion                 | 0.97±0.85         | 0.93±0.80         | -0.04         | 0.678       |
| Reassurance                | 1.39±1.05         | 1.63±1.09         | +0.25*        | 0.032       |
| Mistrust                   | 0.95±1.06         | 0.61±0.78         | -0.34***      | <0.001      |
| Total CSS (mean item, 0-4) | 1.20±0.55         | 1.18±0.57         | -0.02         | 0.708       |

\* $p < 0.05$ ; \*\*\*  $p < 0.001$ . Δ = Wave 2 minus Wave 1 mean. CSS domain scores: mean of constituent items, range 0-4. A mean item score of 1.20 corresponds to a summed score of 18.0 on the conventional 0-60 CSS scale (multiply by 15 to convert). Δ is computed from unrounded means; minor differences from the rounded Wave 1/Wave 2 values shown are due to rounding.

**Table 3: CSS-15 Domain Scores by AI-Use Status: Descriptive Effect Sizes (Pooled Two-Wave Analysis)**

| Domain        | AI<br>(n=164)<br>Mean ± SD | Users<br>Non-Users<br>(n=36)<br>Mean ± SD | Cohen's<br>d† |
|---------------|----------------------------|-------------------------------------------|---------------|
| Excessiveness | 1.91±0.88                  | 1.07±0.83                                 | 0.96          |
| Distress      | 1.05±0.88                  | 0.58±0.74                                 | 0.55          |
| Reassurance   | 1.61±1.04                  | 1.06±1.10                                 | 0.53          |
| Compulsion    | 0.99±0.83                  | 0.77±0.82                                 | 0.27          |
| Mistrust      | 0.73±0.90                  | 1.04±1.10                                 | -0.33         |

† Cohen's d values are descriptive effect-size summaries only. No inferential p-values are reported because the same participants contribute observations at both waves. Within-person inferential tests are reported in Table 4. Effect-size interpretation: trivial <0.2, small 0.2-0.5, medium 0.5-0.8, large >0.8.

Table 2 shows CSS-15 domain scores at both waves. Excessiveness was the highest-scoring domain at each wave (W1: 1.79±0.94; W2: 1.73±0.92). Two domains shifted significantly between waves: Reassurance rose (Δ = +0.25,  $p = 0.032$ ) and Mistrust fell (Δ = -0.34,  $p < 0.001$ ). Total CSS mean item scores stayed stable across waves (W1: 1.20±0.55; W2: 1.18±0.57;  $p = 0.708$ ), which underscores why the domain-level analysis is informative; a flat total score conceals the offsetting domain-level changes underneath. A mean item score of 1.20 corresponds to a summed score of 18.0 on the conventional 0-60 CSS scale.

Table 3 compares domain scores between AI users and non-users pooled across both waves. AI users scored substantially higher on Excessiveness (1.91±0.88 vs 1.07±0.83;  $d = 0.96$ , a large effect). Distress ( $d = 0.55$ ) and Reassurance ( $d = 0.53$ ) were also moderately higher

**Table 4: Within-Person Domain Change by AI-Use Transition Group**

| Group                | n  | W1 Mean | W2 Mean | $\Delta$ | Cohen's d (p) |
|----------------------|----|---------|---------|----------|---------------|
| <b>Excessiveness</b> |    |         |         |          |               |
| No→Yes               | 12 | 1.19    | 1.42    | +0.22    | 0.37 (0.232)  |
| Yes→No               | 10 | 1.77    | 1.23    | -0.53    | -0.38 (0.259) |
| Yes→Yes              | 71 | 2.00    | 1.93    | -0.07    | NS            |
| <b>Distress</b>      |    |         |         |          |               |
| No→Yes               | 12 | 0.56    | 0.94    | +0.39*   | 0.69 (0.036)  |
| Yes→No               | 10 | 1.23    | 0.83    | -0.40    | -0.41 (0.228) |
| Yes→Yes              | 71 | 1.01    | 1.09    | +0.08    | NS            |
| <b>Reassurance</b>   |    |         |         |          |               |
| No→Yes               | 12 | 1.03    | 1.36    | +0.33    | 0.44 (0.160)  |
| Yes→No               | 10 | 1.37    | 1.20    | -0.17    | NS            |
| <b>Mistrust</b>      |    |         |         |          |               |
| No→Yes               | 12 | 0.97    | 0.56    | -0.42    | -0.37 (0.228) |
| Yes→Yes              | 71 | 0.89    | 0.53    | -0.37**  | -0.38 (0.002) |
| <b>Compulsion</b>    |    |         |         |          |               |
| No→Yes               | 12 | 1.11    | 1.03    | -0.08    | NS            |
| Yes→No               | 10 | 1.33    | 0.83    | -0.50    | -0.50 (0.147) |

\*p < 0.05; \*\* p < 0.01 (paired t-test). NS = not significant. Persistent non-users (No→No, n = 7) and group/domain combinations with no notable change are omitted from the table for clarity. The Yes→Yes Mistrust drop reflects the cohort-wide Mistrust decline shown in Table 2. All four transition groups were tested across all five domains;  $\Delta$  is computed from unrounded means, so small differences from the rounded means shown are due to rounding.

**Table 5: Dose-Response: CSS-15 Domain Scores by Search Frequency (Wave 1, N = 100)**

| Search Frequency | n  | Excessiveness | Distress  | Compulsion | Reassurance | Mistrust  |
|------------------|----|---------------|-----------|------------|-------------|-----------|
| Rarely           | 28 | 1.12±0.70     | 0.52±0.72 | 0.45±0.62  | 0.64±0.81   | 1.11±1.31 |
| Sometimes        | 42 | 1.90±0.91     | 0.92±0.79 | 1.13±0.84  | 1.34±0.91   | 1.05±1.06 |
| Often            | 23 | 2.17±0.78     | 1.23±1.06 | 1.26±0.86  | 1.97±0.86   | 0.75±0.73 |
| Always           | 7  | 2.57±1.03     | 1.52±1.02 | 1.14±1.00  | 2.71±0.85   | 0.43±0.50 |
| Spearman $\rho$  |    | 0.47***       | 0.32**    | 0.35***    | 0.57***     | -0.09 NS  |

Values are mean±SD. \*\* p < 0.01; \*\*\* p < 0.001; NS, not significant. Significance markers apply to the Spearman  $\rho$  row.

in AI users. The difference for Compulsion was small ( $d = 0.27$ ), and Mistrust differed slightly in the opposite direction ( $d = -0.33$ ). These are descriptive effect sizes; no inferential p-values are reported because the same students contribute data at both waves.

Table 4 shows within-person domain change by transition group. Among the 12 students who newly adopted AI between waves, Distress increased significantly (0.56 to 0.94;  $\Delta = +0.39$ ,  $d = 0.69$ ,  $p = 0.036$ ), and no other domain in this group changed significantly. Students who discontinued AI use ( $n = 10$ ) showed no significant within-person change in any domain. Among persistent users (Yes→Yes,  $n = 71$ ), Mistrust fell significantly ( $\Delta = -0.37$ ,  $p = 0.002$ ), but this mirrors the cohort-wide Mistrust decline shown in Table 2 and is unlikely to reflect an AI-specific effect. Given the small group sizes for new adopters and discontinued users, these within-person results are exploratory. All four transition groups were tested across all five domains; the complete group-by-domain results can be provided as a supplementary table on request.

Table 5 shows domain scores by search frequency at Wave 1. Excessiveness rose steadily across the four frequency categories, from 1.12±0.70 in students who rarely searched to 2.57±1.03 in those who always did, a 1.45-unit increase across the spectrum. Significant graded relationships with search frequency were con-

firmed by Spearman correlation for Excessiveness ( $\rho = 0.47$ ), Reassurance ( $\rho = 0.57$ ), Compulsion ( $\rho = 0.35$ ) and Distress ( $\rho = 0.32$ ; all  $p \leq 0.001$ ), whereas Mistrust showed none ( $\rho = -0.09$ ,  $p = 0.356$ ).

Searching symptoms before consulting a doctor was strongly associated with Excessiveness at Wave 1 ( $d = 1.04$ ; symptom-searchers: 2.01±0.87 vs non-searchers: 1.12±0.84), comparable in magnitude to the pooled AI-use effect. Second-year students had lower Mistrust and higher Reassurance scores than first-year students, consistent with growing trust in physicians as training progresses. Gender showed no significant domain differences. In a multiple regression, Wave 1 AI use, search frequency, symptom-searching, year of study, gender and baseline Excessiveness together accounted for 24.4% of the variance in Wave 2 Excessiveness ( $R^2 = 0.244$ ,  $F(6,93) = 5.00$ ,  $p < 0.001$ ); only year of study and baseline Excessiveness reached significance as individual predictors.

## DISCUSSION

**Principal Finding:** AI use was associated with cyberchondria, but unevenly across the five domains. In pooled between-group comparisons, AI users scored substantially higher than non-users on Excessiveness, Distress and Reassurance, while Compulsion and Mis-

trust differed little. The longitudinal picture was narrower. Among the small group of new adopters, only Distress rose significantly between Wave 1 and Wave 2. Excessiveness, which had shown the largest between-group effect, did not change significantly with AI adoption or discontinuation over the three-month follow-up. One reading of this contrast is that affective responses to health information shift faster than entrenched searching behaviour; replication in larger samples is needed before this can be claimed with confidence.

**Why Distress, Not Excessiveness, Shows Within-Person Change:** There are reasons to expect Excessiveness and Distress to respond on different timescales. Excessiveness captures a stable habit: returning to the same symptom, visiting multiple sites, extending a search past the original question. Habits of this kind do not usually flip in three months. Distress, by contrast, is an affective response to a specific information event. AI tools present health information in a particular way, often confidently structured and listing differential diagnoses that an ordinary search does not surface, and an anxious reaction to such content can plausibly emerge within weeks of starting to use these tools. The between-group Excessiveness association may therefore reflect a pattern that pre-dates the observation window, while the within-person Distress signal may pick up a more immediate effect of starting to use AI.

**Search Frequency as the Stronger Modifiable Target:** The clearest signal in the dataset was not AI use itself but search frequency. Excessiveness rose steadily across the four frequency categories, from 1.12 in students who rarely searched to 2.57 in those who always did ( $p = 0.47$ ,  $p < 0.001$ ), and similar gradients held for Reassurance, Compulsion and Distress. From a public health standpoint this matters, because frequency is more directly modifiable than AI adoption. A medical student is unlikely to give up AI tools entirely, but moving from frequent to occasional searching is a realistic behavioural target. Digital health literacy curricula are likely to have more traction if they address how often and in what context students search, particularly before consulting a doctor, than if they treat AI use as a binary to be encouraged or discouraged.

**Symptom-Searching Before Doctor Consultation as the Dominant Predictor:** One of the largest between-group effects in the dataset came from a single behaviour: searching symptoms before consulting a doctor. At Wave 1, three in four students reported doing this, and pre-searchers scored almost a full standard deviation higher on Excessiveness than students who did not ( $d = 1.04$ ). The behaviour is widespread and largely unaddressed in undergraduate medical education. A useful next question is whether AI tools are now the preferred medium for pre-consultation symptom checking; if so, the AI-specific and symptom-searching effects observed here would converge on a single behavioural pathway.

**Comparison with Existing Literature:** The 81-83% prevalence of AI use in this cohort is high relative to ear-

lier surveys of AI adoption among medical students [8,9]. Two factors plausibly explain this: the rapid uptake of generative AI since 2023, and the unusually high digital engagement of medically literate populations. The domain-selective between-group pattern, with a large effect on Excessiveness, moderate effects on Distress and Reassurance, and null effects on Compulsion and Mistrust, fits with prior evidence that cyberchondria facets reflect different psychological processes [7] and should not be collapsed into a single total score [1]. Indian evidence on cyberchondria in undergraduate medical students remains limited but growing [12], with international cohorts of medical and university students consistently reporting moderate-to-high cyberchondria severity [13,14]. The comparable cyberchondria cohorts cited here are cross-sectional; the present two-wave design adds a within-person dimension to this question. To our knowledge, however, no prior study, in India or elsewhere, has examined AI use as a distinct exposure against domain-level cyberchondria. The present study fills that gap. The Mistrust domain behaved atypically here - no dose-response, an effect opposite in direction to the other four domains, and a decline that appeared cohort-wide rather than AI-specific - a pattern consistent with the weaker factor loading that led to Mistrust being dropped from the CSS-12 [11]; these Mistrust findings should therefore be read with particular caution.

### Strengths and Limitations

The study's strengths are a prospective longitudinal design with 100% retention, explicit ID-based participant matching across waves, domain-level rather than total-score analysis, a four-group AI-use transition classification, effect-size reporting for all key comparisons, and a dose-response analysis of search frequency. The main limitations are the small group sizes for less common transition patterns (notably the 12 new adopters and 10 discontinued users) and the single-institution sample, which limit generalisability and statistical power for the subgroup analyses. Search frequency and pre-consultation symptom-searching were captured with single-item, non-validated self-report categories, and all exposure measures are subject to social-desirability and recall bias. The two waves also fell at different points in the academic calendar (January versus April, the latter nearer end-of-term examinations), so calendar-related stress cannot be separated from the observed Reassurance rise and Mistrust decline. Multi-centre replication in larger cohorts will be needed to establish external validity.

## CONCLUSION

AI-assisted health information seeking was associated with elevations in cyberchondria that were concentrated in the Excessiveness domain. Exploratory within-person analysis, based on a small and underpowered new-adopter subgroup ( $n=12$ ), suggested an increase in Distress. Across the dataset, however, the most consistent

dose-response relationship was with search frequency rather than with AI adoption itself. Digital health literacy training in MBBS curricula should focus on search-frequency behaviour and on the habit of searching symptoms before clinical consultation.

## RECOMMENDATIONS

(1) Among pre-clinical MBBS students in settings similar to this South Indian government medical college, consideration should be given to incorporating digital health literacy content that addresses search-frequency behaviour and pre-consultation symptom searching rather than AI use as a simple yes/no question; these results suggest an association rather than an established causal effect. (2) Future research should measure AI health use in finer detail, including platform, frequency, query type and duration. (3) Quasi-experimental studies are needed to test whether structured guidance on health-search behaviour reduces Excessiveness and Distress scores. (4) Because pre-consultation symptom searching showed the strongest association with Excessiveness in this cohort, behavioural counselling for comparable student populations could reasonably give attention to this habit, pending confirmation in larger, multi-centre samples.

**Individual Author's Contribution:** JRM contributed to the conception and design of the study, data collection, data analysis and interpretation, and manuscript preparation. SD contributed to the conception and design of the study and manuscript preparation. KB contributed to the conception and design of the study and manuscript preparation.

**Availability of data:** The data that support the findings of this study are available from the corresponding author on reasonable request.

**Declaration of Non-use of generative AI Tools:** This article was prepared without the use of generative AI tools for content creation, analysis, or data generation. All findings and interpretations are based solely on the authors' independent work and expertise.

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