Original Paper

Generative AI Use for Mental Health Support Among Students at a UK University: Cross-Sectional Study

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Abstract

Background: Generative AI (GenAI) tools are increasingly used for health information and emotional support, yet little is known about their use for mental health by university students, a population with high digital literacy and elevated mental health need.

Objective: To estimate the prevalence of GenAI use for mental health support among respondents to a survey at a single UK university and to identify demographic and well-being characteristics associated with use.

Methods: Cross-sectional online survey of students at a large UK university. The primary outcome was self-reported GenAI use for mental health support in the past 6 months. Well-being was assessed using the Short Warwick-Edinburgh Mental Wellbeing Scale. Associations were examined using multivariable modified Poisson regression to estimate adjusted prevalence ratios.

Results: Of 22,207 students invited, 2020 responded (response rate 9.1%). Among respondents, 25.0% (n=503) reported GenAI use for mental health support in the past 6 months. The most common reasons were advice when emotionally distressed (n=380, 19.3%), insights into mental health (n=256, 12.7%), and using GenAI as a personal therapist or coach (n=173, 8.6%); 2.7% (n=54) reported using GenAI to seek support when experiencing thoughts of self-harm. Use was more common among students aged 26-29 years, those identifying as Asian, students reporting a declared disability, students enrolled in management programs, and those with lower well-being.

Conclusions: Among respondents at a UK university, approximately one in four reported using GenAI for mental health support. Use was concentrated among students reporting poorer well-being and disability, suggesting that GenAI may function as an informal help-seeking pathway. Universities and health services should anticipate GenAI as a help-seeking pathway and ensure appropriate guidance, integration with existing services, and safeguards to support safe and equitable use.

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Keywords: generative artificial intelligence; digital mental health; university students; help-seeking behavior; mental health; large language models

Introduction

Background

University students experience high rates of mental health difficulties, including depressive symptoms, which affect approximately 25% of students [1], with even higher rates during the first year [2]. Despite substantial need, only around 14% of students engage with formal mental health services [3]. This gap between need and service uptake has prompted increasing interest in alternative or supplementary support pathways.

Generative AI (GenAI) tools, including large language models (LLMs; eg, ChatGPT), are increasingly shaping how individuals seek health information, emotional support, and guidance [4]. Although not designed for clinical mental health care, these tools can simulate therapeutic dialog, provide coping suggestions, and offer immediate, anonymous responses, and have been reported to be acceptable to users [5]. These characteristics may make them particularly attractive to university students, a group with high mental health needs [1,2].

Empirical evidence on the use of AI-based tools for mental health among students remains limited. Studies conducted prior to the widespread public adoption of contemporary LLMs likely underestimate current use, as they often focused on earlier, rule-based or narrowly scripted chatbots rather than general purpose GenAI systems [6].

Few large studies have examined the prevalence and predictors of GenAI use specifically for mental health support among UK university students. A recent cross-sectional study of 1058 US adolescents and young adults found that 13% reported using GenAI for mental health advice, with higher rates among those aged 18-21 years (22.2%) [7]. However, this study focuses on adolescents or mixed youth samples rather than university students, and limited comparable data exist for UK student populations. As GenAI tools become increasingly embedded within everyday digital practices, understanding their role within student mental health ecosystems is important for universities, health services, and policymakers.

Objective

To estimate the prevalence of GenAI use for mental health support among respondents to a student survey at a single UK university and to identify demographic and well-being characteristics associated with such use. We additionally aimed to characterize the primary reasons for GenAI use and hypothesized that students with lower well-being would be more likely to report GenAI use for mental health support.

Methods

Study Design

This cross-sectional study is reported in accordance with the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) checklist for cross-sectional studies [8] and the CHERRIES (Checklist for Reporting Results of Internet E-Surveys) guidelines for online survey research [9].

Ethical Considerations

The study was approved by the University of Bath's ethics committee (approval ID: 0230-16615). All participants provided informed electronic consent prior to completing the survey.

Setting

Data were collected using JISC Online Surveys administered by the University of Bath Student Engagement Team. The survey platform complied with UK General Data Protection Regulation (GDPR) requirements. The survey was sent out to all registered students at the university during the first semester of the academic year, between October 20, 2025, and November 9, 2025, and could be completed on desktop or mobile devices. All registered undergraduate and postgraduate students (n=22 207) were invited via university mailing lists, social media advertisements, and course announcements.

Participants

Participants were eligible if they were currently enrolled as a student at the University of Bath, aged 16 years or over, had internet access, and were able to complete the survey in English. Participants who completed the survey were eligible for entry into a prize draw (£500, two £100 prizes, and two £50 prizes; £1=US $1.34, as of October 2026). Survey links were single-use and authenticated through the university email system to prevent duplicate and unverified submissions.

Data Sources and Measurement

The survey was adapted from the university's annual student well-being survey, administered continuously since 2017, and was developed in collaboration with the University of Bath Student Support Services Student Engagement Team, and the Students' Union. Additional items were added to assess AI use for mental health. Item development was informed by prior research on digital mental health behaviors [10]. Participants could skip any survey item; no items were mandatory.

Variables

All variables were self-reported through the online survey platform. The survey captured sociodemographic characteristics. Primary and secondary outcomes capturing AI use were assessed using items adapted from Cross et al [10]. The primary outcome was self-reported use of AI for mental health in the past 6 months (yes/no), assessed via the item: "Have you used AI in the last 6 months in relation to your mental health?" Secondary outcomes included specific reasons for AI use, assessed via the item: "What do you use AI tools for?," for which respondents could select multiple responses (ie, "getting quick advice when emotionally distressed," "as a personal therapist or coach," "provide insights into my mental health and emotions," "learning more about mental health," "getting advice about how to help others," "getting support when having thoughts of harming yourself," "information about where to get help"). Well-being was assessed using the Short Warwick–Edinburgh Mental Wellbeing Scale (SWEMWBS), a validated 7-item measure of positive mental well-being over the past 2 weeks. Items are rated on a 5-point Likert scale ranging from 1 ("none of the time") to 5 ("all of the time"), with higher scores indicating better well-being [11] . Demographic variables

included age group, sex, ethnicity (UK Office for National Statistics categories), degree level, faculty, disability status, study mode, and fee status (United Kingdom vs international). Disability status was assessed using a single self-report item ("Do you consider yourself to have a disability?"), with response options of "Yes," "No," and "Prefer not to say."

Analysis

Statistical analyses were conducted in R (version 4.5.2; R Core Team, 2025) using RStudio (version 2025.09.2; Posit Software, 2025). Age was categorized into predefined university demographic groups (Under 18, 18-21, 22-25, 26-29, and ≥30 years) to align with internal reporting conventions. In line with established guidance, SWEMWBS metric scores were categorized and analyzed as a categorical variable, indicating very low (≤17), low (18–20), average (21–27), and high (≥28) well-being. Participant characteristics were summarized using descriptive statistics. The primary outcome was self-reported use of AI for mental health purposes in the past 6 months. Associations between participant characteristics and AI use were examined using multivariable modified Poisson regression with robust standard errors, which allows direct estimation of adjusted prevalence ratios for a binary outcome in cross-sectional data. Reference categories were selected to facilitate interpretation, generally using the most prevalent category or a conceptually meaningful comparison group (eg, average well-being for SWEMWBS). Covariates were selected a priori to examine their associations with GenAI use, informed by previous research examining demographic, educational, and mental health–related characteristics associated with mental health service utilization and help-seeking behaviors among university students [3,12]. These included age, gender, ethnicity, fee status, study level, study mode, disability status, and well-being. The analysis plan was not formally preregistered. Results are presented as adjusted prevalence ratios (aPRs) with 95% CIs. Complete-case analysis was used due to low missing data. As this was a census of all enrolled students, no a priori sample size calculation was performed. All complete responses were included in analyses.

Results

Of 22,207 enrolled students contacted, 2020 responded (response rate=9.1%). Participant characteristics are presented in Table 1. Missing data were less than 1% across variables. Most participants were aged 18-21 years (n=1279, 63.3%) and identified as female (n=1224, 60.6%); 21.9% (n=442) reported a declared disability. The sample was predominantly White (n=1281, 63.4%), with representation from Asian (n=440, 21.8%), mixed (n=135, 6.7%), Black (n=64, 3.2%), Arab (n=36, 1.8%), and other ethnic groups. Most participants were undergraduates (n=1435, 71.0%), with postgraduate taught (n=327, 16.2%) and postgraduate research (n=212, 10.5%) students also represented. Most students reported average (n=970, 48.1%) or low (n=800, 39.7%) well-being, with a smaller proportion reporting very low well-being (n=161, 8.0%). Most students reported knowing where to seek mental health support (n=1573, 77.9%), and a similar proportion reported willingness to seek help (n=1582, 78.3%). Some differences in respondent characteristics were observed when compared with institutional enrolment data from December 2025. Those identifying as female were overrepresented among survey respondents (1224/2020, 60.6% compared with 9890/21,452, 46% of the university population), while undergraduate students were modestly underrepresented (1435/2020, 71.0% vs 16,401/21,452, 76%) and postgraduate research students were modestly overrepresented (212/2020, 10.5% vs 1600/21,452, 7%). Distributions were more closely aligned for declared disability (442/2020, 21.9% vs 3980/21,452, 19%), White ethnicity (1281/2020, 63.4% vs 13,290/21,452, 62%), and faculty of study, where absolute differences ranged from 1.2 to 2.8 percentage points.

Table 1. Sociodemographic and well-being characteristics of participating students.

Sample characteristics	Students (N=2020), n (%)
Age (years)	
Under 18	14 (0.7)
18-21	1279 (63.3)
22-25	386 (19.1)
26-29	123 (6.1)
30 and over	201 (10.0)
Prefer not to say	7 (0.4)
Missing	10 (0.5)
Sex	
Female	1224 (60.6)
Male	790 (39.1)
Other	3 (0.2)
Missing	3 (0.2)
Disability	
No disability declared	1577 (78.1)

Sample characteristics	Students (N=2020), n (%)
Disability declared	442 (21.9)
Missing	1 (0.1)
Fee status	
United Kingdom	1510 (74.8)
Overseas	502 (24.9)
European Union	7 (0.4)
Missing	1 (0.1)
Ethnicity	
White	1281 (63.4)
Asian	440 (21.8)
Mixed	135 (6.7)
Black	64 (3.2)
Arab	36 (1.8)
Prefer not to say	35 (1.7)
Other	26 (1.3)
Missing	3 (0.2)
Degree level	
Undergraduate	1435 (71.0)
Postgraduate taught	327 (16.2)
Postgraduate research	212 (10.5)
Other	45 (2.2)
Missing	1 (0.1)
Faculty	
Humanities and Social Sciences	731 (36.2)
Science	663 (32.8)
Engineering and Design	340 (16.8)
School of Management	285 (14.1)
Missing	1 (0.1)
SWEMWBS score[a]	
Very low	161 (8.0)
Low	800 (39.7)
Average	970 (48.1)
High	86 (4.3)
Missing	3 (0.1)
Knowledge of where to get support	
Yes	1573 (77.9)
No	396 (19.6)
Prefer not to say	36 (1.8)
Missing	15 (0.7)
Willingness to seek help	
Yes	1582 (78.3)
No	290 (14.4)
Prefer not to say	130 (6.4)
Missing	18 (0.9)

[a]SWEMWBS: Short Warwick–Edinburgh Mental Wellbeing Scale.

A total of 2020 respondents completed the survey, but as not all respondents completed all survey questions, the total number of responses for each question varies.

Around one-quarter of respondents (n=503, 25.0%) reported using AI for mental health purposes in the past 6 months, while the majority (n=1508, 75.0%) had not (Figure 1). The most frequently reported reasons for AI use included seeking advice when emotionally distressed (n=390, 19.3%), gaining insights into their mental health (n=256, 12.7%), and learning more about mental health (n=182, 9.0%). Smaller proportions reported using AI as a personal therapist or coach

(n=173, 8.6%), obtaining advice on helping others (n=167, 8.3%), or seeking information about where to get help (n=90, 4.5%). A minority (n=54, 2.7%) reported using AI for support related to self-harm (Figure 2). Participants could select multiple responses.

Figure 1. AI use in the last 6 months.

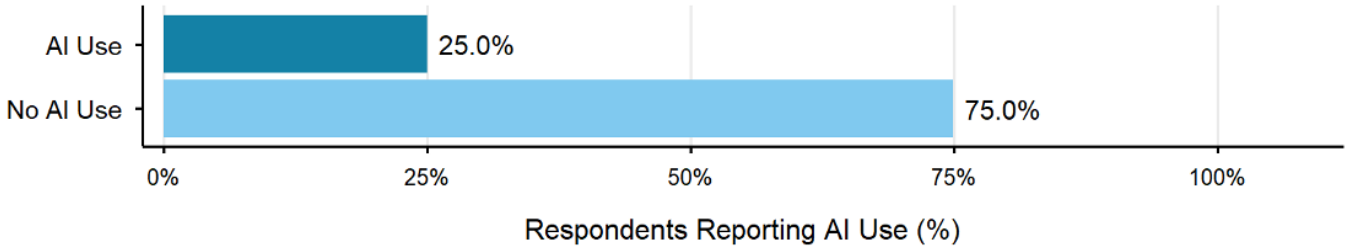
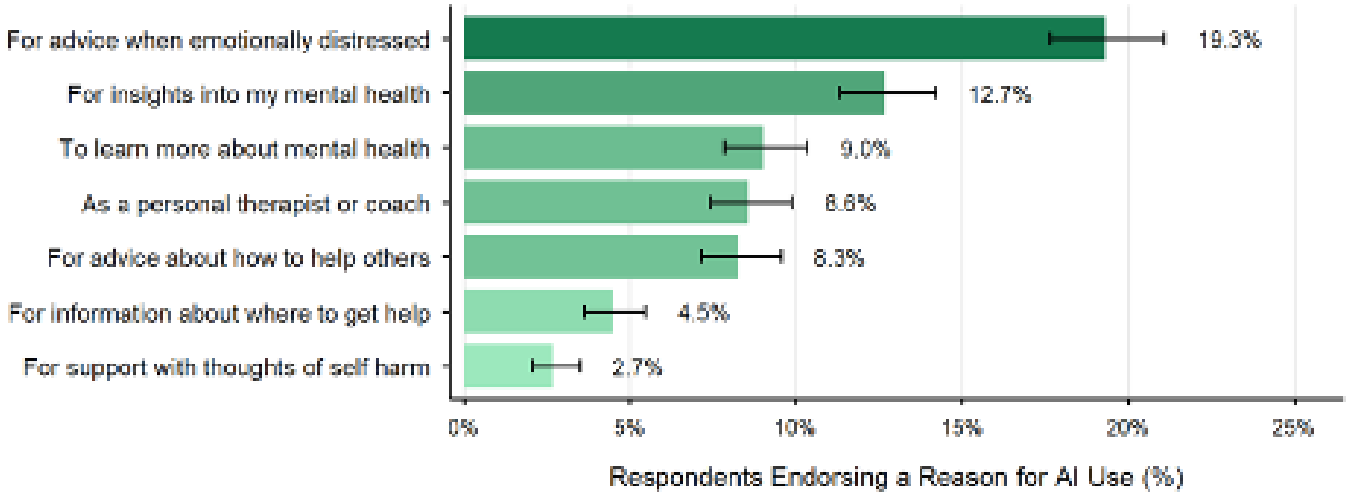


Figure 2. Mental health–related reasons for using AI.



Prevalence of AI use for mental health in the past 6 months varied across demographic and well-being groups (Figure 3). By age, use was highest among students aged 26-29 years (47/123, 38.2%; 95% CI 30.1%-47.0%) and lowest among those aged 30 years and over (45/201, 22.4%; 95% CI 17.2%-28.6%). Among students aged under 18 years, prevalence was also high (6/14, 42.9%; 95% CI 21.4%-67.4%), although estimates were imprecise because of small numbers. By degree level, prevalence was highest among postgraduate taught students (101/327, 30.9%; 95% CI 26.1%-36.1%) and lowest among postgraduate research students (47/212, 22.2%; 95% CI 17.1%-28.2%). Across faculties, use was highest in the School of Management (106/285, 37.2%; 95% CI 31.8%-42.9%) and lowest in Engineering and Design (68/340, 20.0%; 95% CI 16.1%-24.6%). Students who declared a disability reported higher use (131/442, 29.6%; 95% CI 25.6%-34.1%) than those without a declared disability (372/1577, 23.6%; 95% CI 21.6%-25.7%). Use was higher among overseas students (159/502, 31.7%; 95% CI 27.8%-35.9%) than UK students (342/1510, 22.6%; 95% CI 20.6%-24.8%). By well-being category, prevalence was highest among students with very low well-being (56/152, 36.8%; 95% CI 29.6%-44.7%) and lowest among those with average well-being (183/960, 19.1%; 95% CI 16.7%-21.7%).

In multivariable regression analyses (Figure 4), several factors were independently associated with AI use for mental health support in the past 6 months. Students aged 26-29 years were more likely to report AI use for mental health support compared with those aged 18-21 years (aPR 1.63, 95% CI 1.13-2.34; *P*=.009). Compared with White students, those identifying as Asian were more likely to report AI use for mental health support (aPR 1.26, 95% CI 1.01-1.58; *P*=.04), while students identifying as Black showed lower prevalence, although this did not reach conventional levels of statistical significance (aPR 0.58, 95% CI 0.32-1.04; *P*=.07). Faculty of study was also associated with AI use. Students in Engineering and Design were less likely to report AI use compared with those in Humanities and Social Sciences (aPR 0.77, 95% CI 0.60-0.98; *P*=.04), whereas students in the School of Management were around 33% more likely to report AI use (aPR 1.33, 95% CI 1.08-1.64; *P*=.007). Students who reported a declared disability had a higher prevalence of AI use than those without a declared disability (aPR 1.29, 95% CI 1.08-1.55; *P*=.006). Well-being showed a strong graded association: compared with students reporting average well-being, those with very low well-being were approximately twice as likely to report AI use (aPR=2.01, 95% CI 1.57-2.58; *P*<.001), and those with low well-being were around 56% more likely to report AI use (aPR=1.56,

95% CI 1.32-1.85; *P*<.001). There was no evidence of association with sex, degree level, fee status, or high well-being.

Figure 3. Using AI for mental health support in the last 6 months by demographic group. Bars show the percentage of respondents reporting AI use for mental health in the last 6 months with 95% CIs. “Prefer not to say” responses are excluded. Smaller categories may have wider uncertainty.

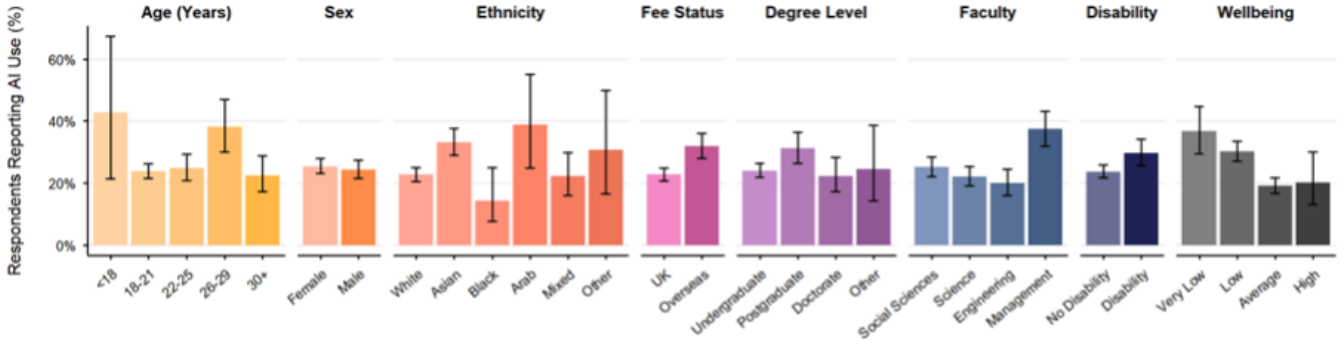
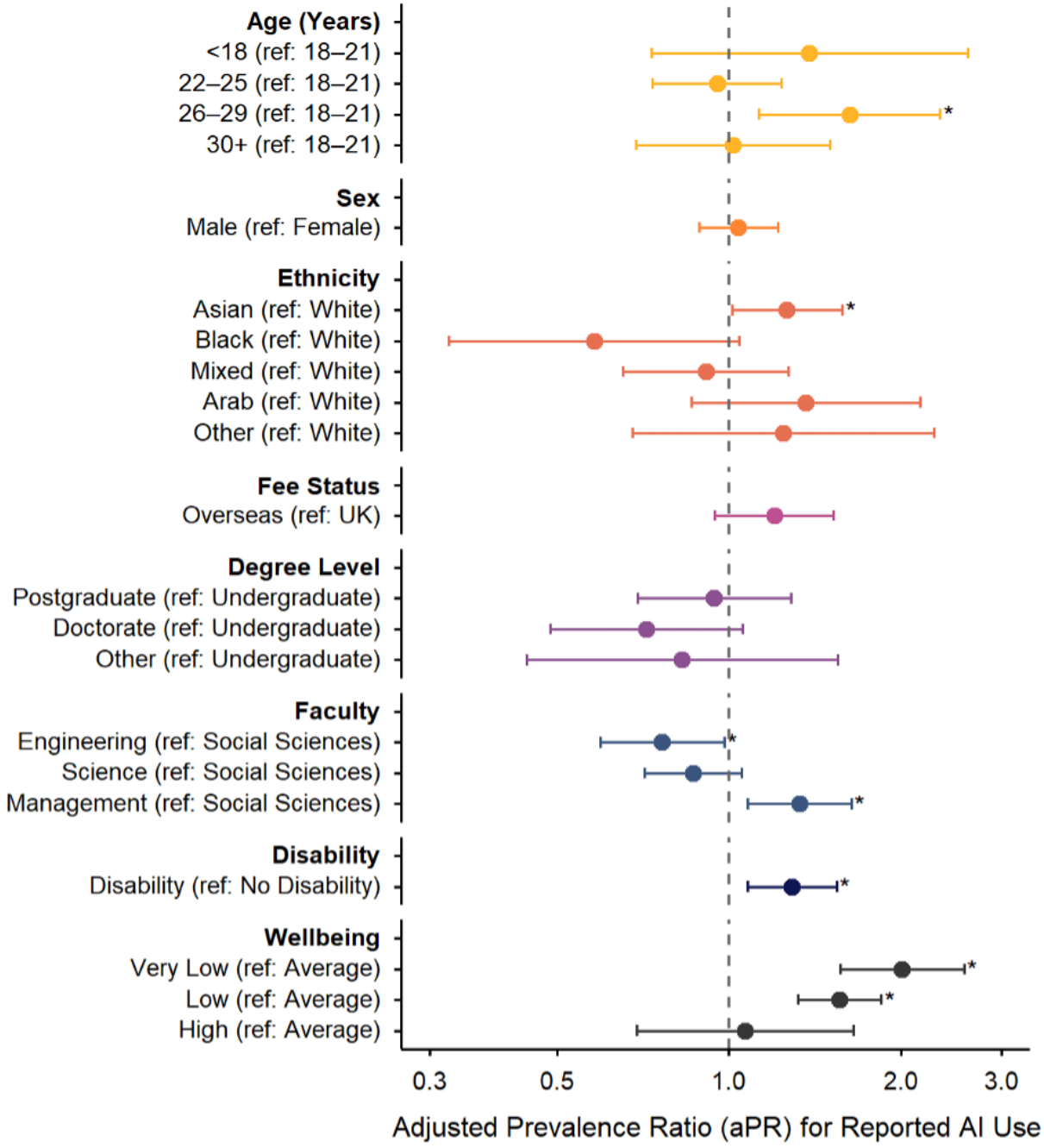


Figure 4. Adjusted prevalence ratios (aPRs) for predictors of AI for mental health support in the last 6 months. aPRs were estimated using multivariable modified Poisson regression with robust standard errors. Reference categories are indicated in facet labels. Error bars represent 95% CIs. Well-being was analyzed categorically, with average well-being as the reference category. Categories with very small cell counts or "Prefer not to say" responses were included in the model but excluded from display to aid interpretation. *P<.05.



Discussion

In this large survey of UK university students, approximately one in four participants (25%) reported using AI tools for mental health support in the past 6 months. The most reported uses were seeking advice when emotionally distressed and gaining insights into mental health, with a minority reporting use to seek support when experiencing thoughts of self-harm. Respondents with lower well-being were substantially more likely to report AI use. This pattern is consistent with emerging evidence suggesting higher GenAI use among individuals with poorer mental health [13]. Higher use was also observed among students with a declared disability and among those studying in the School of Management, whereas lower use was observed among students in Engineering and Design. A lower prevalence was also observed among those identifying as Black, although this association was not statistically significant. Together, these findings suggest that GenAI is functioning as an informal, low-threshold support pathway within student mental health ecosystems, particularly

among those with elevated mental health burden or declared disabilities. This observation aligns with broader discussions in mental health care regarding the promise and risks of LLMs, including concerns about hallucinations, bias, privacy and safeguarding [14].

Our findings align with emerging international evidence on AI use for emotional support. McBain et al [7] reported that 13% of US adolescents and young adults used GenAI for mental health advice, with higher prevalence among older youth (18-21 years). Prevalence in our student population was higher, which may reflect differences in population, context, or timing of data collection. Notably, our primary item used broader phrasing ("in relation to mental health"), whereas prior studies have used more specific prompts (eg, seeking advice when feeling sad, angry, or nervous), which may contribute to variation in estimates. Pre-LLM chatbot studies (eg, Gbollie et al [6]) reported much lower engagement (~4.5%), which highlights how LLM availability has rapidly changed help-seeking behaviors. These findings indicate that GenAI represents an emerging informal help-seeking pathway among students, operating alongside formal sources of support such as university well-being services and clinicians [15]. However, this is despite limited evidence on safety, effectiveness, or appropriate use of AI [4]. The inclusion of both a broad primary item and more specific follow-up items in the present study suggests that GenAI use spans a continuum from general mental health exploration to more targeted support-seeking behaviors.

Students' use of AI may reflect its immediacy, anonymity, and accessibility, which are features known to appeal to young people experiencing emotional distress [12]. AI tools may also reduce perceived stigma or logistical barriers associated with formal help-seeking. At the same time, differences in uptake suggest that GenAI may reduce barriers for some groups while leaving others less engaged, potentially reflecting concerns about privacy, bias, or cultural relevance. Previous research has reported mixed findings, with some studies identifying barriers to digital mental health engagement among marginalized groups, including concerns about data privacy, cultural relevance, algorithmic bias, and historical mistrust of institutions and technologies [16]. Conversely, Habicht et al reported higher engagement with a digital mental health intervention among some ethnic minority groups [17]. This suggests that patterns of engagement may vary according to the type of digital support, population, and context, rather than reflecting consistently lower engagement among marginalized groups.

A non-trivial minority described using AI for purposes resembling therapeutic support or to seek support when experiencing thoughts of self-harm. Given that GenAI tools are not designed, regulated, or clinically validated to deliver mental health treatment or crisis intervention, this pattern raises important safety considerations. While such use may reflect unmet need or barriers to accessing formal services, it underscores the need for clear guidance and safeguards when individuals experiencing significant distress engage with AI-mediated support. Concerns have been raised previously that chatbots do not adequately respond in times of crisis, at times being dismissive or neglecting to provide crisis resources [18]. These patterns underscore the urgency of developing ethical and governance frameworks that acknowledge the real-world use of GenAI outside regulated clinical environments.

These findings have important implications for universities and mental health services. At present, many universities lack explicit guidance or safeguarding frameworks addressing students' use of GenAI for mental health support. A substantial proportion of students are already engaging with these tools, particularly those with poorer well-being and declared disabilities. Therefore, institutions need to acknowledge AI as an emerging help-seeking pathway among students and provide clear guidance to students that addresses safety, privacy, and limitations of AI-generated advice. Brief digital literacy components embedded within existing student support pathways may help students engage with these tools more safely. Ongoing monitoring of patterns of GenAI use may also help universities adapt student support provision in an evolving digital landscape.

This study has several limitations. First, the response rate was only 9.1%, introducing potential nonresponse and selection bias. Students experiencing mental health difficulties may have been more likely to participate, potentially inflating prevalence estimates, while students less engaged with university communications may be underrepresented. However, this is typical for large voluntary university-wide online surveys [19], and comparisons with institutional enrolment statistics suggested broadly similar distributions across key demographic characteristics, apart from an overrepresentation of women. Second, the survey was conducted at a single UK institution, which may limit generalizability to universities with different demographic or cultural contexts. Although the sample included students from multiple ethnic and international backgrounds and across all faculties, patterns of GenAI use may differ in institutions with alternative demographic profiles or student support infrastructures. Third, we did not collect information on which AI tools were used, nor the nature or quality of the outputs students received. Future research should examine not only patterns of AI use, but also the content, accuracy, and safety of AI outputs, including how students interpret and act on this information over time. Fourth, the primary measure of AI use used relatively broad phrasing ("in relation to your mental health"), which may capture a wide range of behaviors and may not align directly with more specific prompts. However, secondary items assessing specific reasons for use (eg, advice when emotionally distressed or support when experiencing thoughts of self-harm) provide additional context regarding how students engage with these tools. Fifth, the cross-sectional design precludes conclusions regarding directionality. It remains unclear whether poorer well-being leads to greater GenAI use, whether GenAI use relates to subsequent changes in well-being, or whether both reflect underlying unmet support needs. Sixth, although the hypothesis and covariates were specified prior to examining their associations with GenAI use, the analyses were not formally preregistered, limiting independent verification of these decisions. Finally,

AI use for mental health was self-reported, which may be subject to recall bias or variation in how participants interpreted AI use and its relevance to their mental health. Nonetheless, self-reports remain the most feasible method for capturing informal and private GenAI use. Future research should integrate self-reports with objective usage data and examine how students interpret and act on AI-generated advice over time.

In this large survey of UK university students, GenAI tools were used for mental health support by approximately one in four respondents, with higher uptake among those reporting poorer well-being and among students with a declared disability. These findings indicate that GenAI is already functioning as an informal support pathway within student mental health ecosystems. Universities and health services should consider how to acknowledge and respond to this emerging behavior to support safe and appropriate use.

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Generative AI Use

During manuscript preparation, the authors used ChatGPT to support language editing and improve clarity. These tools were not used for data analysis, interpretation, or the generation of scientific insights or conclusions. All content was reviewed, edited, and approved by the authors, who take full responsibility for the accuracy and integrity of the work.

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Data Availability

Deidentified individual participant data are not publicly available due to the sensitive nature of the data and the risk of reidentification within a single-institution student population. Requests for access to aggregate data may be considered by the corresponding author, subject to institutional data governance procedures and ethical approval.

Authors' Contributions

JL: conceptualization; methodology; investigation; data curation; formal analysis; writing – original draft; writing – review & editing; supervision.
NM: formal analysis; writing – review & editing.
ML: methodology; interpretation of findings; writing – review & editing.
NG: methodology; interpretation of findings; writing – review & editing.
GT: interpretation of findings; writing – review & editing.
MJL: conceptualization; methodology; supervision; writing – review & editing.
All authors reviewed and approved the final manuscript and agree to be accountable for all aspects of the work.

Conflicts of Interest

None declared.

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Abbreviations

aPR: adjusted prevalence ratio
CHERRIES: Checklist for Reporting Results of Internet E-Surveys
GDPR: General Data Protection Regulation
GenAI: generative AI
LLM: large language model
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology
SWEMWBS: Short Warwick–Edinburgh Mental Wellbeing Scale

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