

Learning to Think with AI: A Survey on Health Professional Students' Use of Generative AI During Clinical Placements

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Abstract

Background: Generative artificial intelligence (GenAI) has rapidly expanded in higher education and clinical practice. Large language models such as ChatGPT are widely adopted by health profession students for learning and writing tasks. However, little is known about how these tools are mobilized during clinical placements, a critical stage of training where students face high cognitive demands and increasing responsibility for patient care.

Objective: This study aimed to map self-reported uses of GenAI during clinical placements, assess perceived benefits and risks, and identify training and governance needs.

Methods: We conducted a cross-sectional online survey at Université Grenoble Alpes (France) from June to September 2025. Eligible participants were students in medicine, pharmacy, nursing, midwifery, or physiotherapy who were currently in, or had completed within the past 18 months, a clinical placement. The 61-item questionnaire included closed and open-ended questions. A composite maturity score classified respondents as Minimal, Limited, Moderate, or High. Descriptive statistics and trend tests were used for analysis.

Results: Among 388 respondents (79% female; 56% nursing, 18% medicine, 17% pharmacy, 6% midwifery, 3% physiotherapy), 53% reported using GenAI during placements. Uptake was lowest in midwifery (26%) and rose markedly with maturity (9% Minimal vs 76% High; $P<.001$). Students mainly used GenAI for information retrieval (78%), bibliographic search (75%), and translation/rephrasing (71%). Clinical-facing tasks such as case simulation (55%), drafting patient documents (38%), or preparing patient communication (38%) were less frequent, with fewer than 15% reporting weekly use. Most students avoided entering patient identifiers, but 23% acknowledged at least one disclosure, and 47% reported sharing anonymized medical data. Benefits were most often perceived for documentation support (81%) and information access (69%). Risks included dependence (91%), erosion of skills (85%), and confidentiality breaches (87%). Students highlighted strong needs for ethics/regulation training (78%), best-practice guidance (78%), profession-specific coaching (74%), and human-AI collaboration (73%).

Conclusions: GenAI is already embedded in the daily practices of health profession students during placements, primarily as a tool for documentation and information management. While students recognize its utility, they also express concerns about dependence, skills, and confidentiality. These findings underscore the urgent need for structured curricula and governance frameworks to support responsible and patient-centered integration of GenAI into clinical education.

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Original Manuscript

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Abstract

Background

Generative artificial intelligence (GenAI) has rapidly expanded in higher education and clinical practice. Large language models such as ChatGPT are widely adopted by health profession students for learning and writing tasks. However, little is known about how these tools are mobilized during clinical placements, a critical stage of training where students face high cognitive demands and increasing responsibility for patient care.

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Results

Among 388 respondents (79% female; 56% nursing, 18% medicine, 17% pharmacy, 6% midwifery, 3% physiotherapy), 53% reported using GenAI during placements. Uptake was lowest in midwifery (26%) and rose markedly with maturity (9% Minimal vs 76% High; $P<.001$). Students mainly used GenAI for information retrieval (78%), bibliographic search (75%), and translation/rephrasing (71%). Clinical-facing tasks such as case simulation (55%), drafting patient documents (38%), or preparing patient communication (38%) were less frequent, with fewer than 15% reporting weekly use. Most students avoided entering patient identifiers, but 23% acknowledged at least one disclosure, and 47% reported sharing anonymized medical data. Benefits were most often perceived for documentation support (81%) and information access (69%). Risks included dependence (91%), erosion of skills (85%), and confidentiality breaches (87%). Students highlighted strong needs for ethics/regulation training (78%), best-practice guidance (78%), profession-specific coaching (74%), and human-AI collaboration (73%).

Conclusions

GenAI is already embedded in the daily practices of health profession students during placements, primarily as a tool for documentation and information management. While students recognize its utility, they also express concerns about dependence, skills, and confidentiality. These findings underscore the urgent need for structured curricula and governance frameworks to support responsible and patient-centered integration of GenAI into clinical education.

Keywords: generative artificial intelligence; AI use; health professional students; clinical placements; medical education; ethics

Introduction

Generative artificial intelligence (GenAI) has entered the global health landscape at an unprecedented pace. The widely cited example of ChatGPT, which in 2023 achieved passing scores on all three components of the United States Medical Licensing Examination demonstrated the capacity of large language models (LLMs) to engage with complex medical knowledge. Concurrently, adoption among health professional students has expanded rapidly. In the U.S., just over half of medical students (52%) reported using ChatGPT for medical school-related tasks, based on a survey of 415 students, with about one in six doing so on a weekly basis [1]. In Israel, 86% of undergraduate students from medicine, nursing, and allied health professions reported being familiar with ChatGPT [2]. Across Europe, a recent survey on 487 medical students across Germany, Austria, and Switzerland revealed that 38.8% of them reported prior experience with AI chatbots such as ChatGPT [3]. In nursing, an umbrella review emphasized both opportunities and substantial pedagogical, ethical, and organizational challenges in integrating AI into education and practice [4]. Consistently, a qualitative study among undergraduate nursing students found that while GenAI was valued as a supportive learning aid, students also expressed concerns over dependency, weakened critical thinking, and threats to academic integrity [5]. In Italy, nearly all physiotherapy students ($\approx 95.3\%$) were aware of AI chatbots, though more than half reported never using them in academic settings [6].

From an educational perspective, three primary applications of GenAI have been identified: the generation and reformulation of academic content, instant adaptive tutoring, and participation in simulation or problem-based learning scenarios [7–9]. A recent systematic review further synthesized evidence across health professional education, confirming the growing influence of GenAI on student learning, particularly in acquisition, inquiry, practice, and production [10]. Importantly, this growing body of evidence extends to experimental research, with a randomized controlled trial in Norway reporting a modest improvement in knowledge test performance when pharmacy students had access to ChatGPT, although the effect did not reach statistical significance [11]. However, this rapid adoption is unfolding amid a marked institutional vacuum: more than 60% of surveyed pharmacy students reported no formal curricular exposure to GenAI [12], while in 2024 an analysis of 116 U.S. research universities found that less than half provided classroom guidance and many still lacked formal institutional policies [13]. As a result, health professional education is evolving in a state of continuous adaptation, where the promising capabilities of GenAI coexist with substantial risks, including facilitated plagiarism, over-reliance, diminished critical thinking, weakened communication, and threats to the development of clinical reasoning and problem-solving skills [14]. Beyond classroom-based learning, the formation of health professionals also depends heavily on clinical practice, as their training does not take place solely in lecture halls but largely through clinical internships. These so-called “clinical placements”, while essential to professional development, place students in a dual role: learning in real-world conditions while gradually assuming responsibility for patient care. Such placements are frequently marked by heightened stress, significant emotional demands, feelings of inadequacy [15,16], and, in some cases, early signs of burnout [17]. Meanwhile, in clinical practice, GenAI is increasingly being applied across

healthcare settings such as hospitals, clinics, private practices, and pharmacies. Recent reports describe its use to accelerate documentation, simplify radiology reports, draft consultation letters, and even support aspects of diagnostic reasoning [18,19]. An integrative review in nursing similarly highlighted applications of AI across education, clinical practice, workload management, and professional perceptions, pointing to opportunities but also to enduring structural and ethical challenges [20]. In this environment, health professional students in clinical placements are likely to turn to GenAI to ease their daily workload such as checking information, translating a consent form, or rephrasing a discharge summary. While such assistance can provide immediate support when human feedback is unavailable, it also raises concerns about overreliance, the weakening of critical learning processes, and the potential for errors.

A recent survey found that one in five UK general practitioners reported using GenAI, most commonly to generate documentation after patient encounters. Clinicians acknowledged its potential to reduce administrative burden but also raised concerns regarding patient safety, data privacy, and the risk of errors [21]. Other authors caution, however, that adoption may remain limited or prove transient in the absence of robust clinical validation [22]. A clear point of convergence thus emerges. Health professional students in clinical placements stand at the intersection of three evolving contexts: higher education, where GenAI is rapidly becoming mainstream; clinical environments, where healthcare professionals are beginning to adopt it; and a learning experience often marked by uncertainty, stress, and substantial cognitive demands. Yet, to the best of our knowledge, no survey has systematically examined how trainees use GenAI, what motivates their engagement, the benefits they perceive, or the specific risks associated with this pivotal stage of professional development. To address this gap, an anonymous survey was conducted among 388 health professional students from multiple healthcare programs at the Université Grenoble Alpes (France), all of whom had recently completed or were currently engaged in clinical internships. The survey examined patterns of GenAI use and non-use, the tools and tasks involved, and the handling of personal and medical information. It also explored perceived benefits, risks, and ethical concerns, as well as self-reported competence, prior training, and expressed needs for further courses, support, and resources.

Methods

Study design

We conducted a descriptive cross-sectional study in the form of an online survey targeting health professional students at Université Grenoble Alpes (France). The objective was to document actual use, perceived benefits and risks, as well as training needs related to GenAI in the context of clinical placements. Data collection took place between June 1st and September 1st, 2025.

Ethics approval

This study has received ethical approval from the "Ethics Committee for the Integrity and Ethics of Research in Health Professions Education" of the "*Société Internationale Francophone d'Education Médicale*" (Notice n°1905-2025, issued July 17, 2025).

Recruitment procedure

Following approval by the deans of the Faculties of Medicine and Pharmacy at Université Grenoble Alpes, an email invitation was distributed to potential participants enrolled in medical or allied health training programs. In addition, a flyer was posted on student information boards at the entrance of lecture halls and classrooms throughout the recruitment period. Interested students accessed the survey via a LimeSurvey link. Entry into the survey was conditional upon acceptance of an electronic informed consent form, accompanied by an information sheet detailing the study objectives, data confidentiality, voluntary nature of participation, right to withdraw, and potential risks. No personally identifying information was collected. Participation was voluntary, informed

consent was obtained electronically from all participants, and no personally identifiable data were collected.

Data collection

We collected data through an anonymous online survey administered with LimeSurvey. Students interested in the study were invited to access the anonymous link, which contained 61 items: 18 single-choice questions, 38 single-choice questions on a four-point Likert scale (1=strongly disagree to 4=strongly agree), one multiple-choice question, and four open-ended questions. The full survey questionnaire is available in Multimedia Appendix 1.

The items were developed based on four prior studies: Blease et al. [21] on generative AI in primary care, Lobet et al. on the spontaneous use of ChatGPT by university students [23], Karaca et al. on the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) [24], and Boillat et al. on physician and student preparedness for AI [25]. Items were then adapted by consensus to the clinical context.

We organized the instrument into four domains:

- sociodemographic characteristics;
- declared uses of GenAI in clinical practice;
- perceptions and attitudes in clinical contexts;
- knowledge and training related to GenAI.

Two clinical experts validated the content to ensure transdisciplinary relevance, and a pilot test with ten students confirmed intelligibility. Feedback from the pilot was incorporated to produce the final version. The average completion time was 15 minutes.

Construction of the maturity score

We calculated a composite score of self-perceived maturity regarding GenAI based on nine Likert-type items covering three domains: (i) declared knowledge, (ii) digital comfort, and (iii) self-efficacy in academic/professional contexts. Each item was rated on a 4-point scale (1=strongly disagree to 4=strongly agree). For each respondent, the median of the available item responses was computed, yielding a maturity score between 1 and 4. Respondents were then classified into four levels of maturity regarding GenAI: Minimal (1), Limited (2), Moderate (3), and High (4). This categorical variable was used as the primary stratification factor in analyses of perceived benefits and risks.

Data processing and statistical analyses

We reported data in Excel format and analyzed in Python (version 3.11; Python Software Foundation) using pandas (2.2.2), numpy (1.26.4), scipy (1.13.1), statsmodels (0.14.2), and matplotlib (3.9.2). Quantitative variables were described using means or medians with interquartile ranges, while qualitative variables were presented as counts and percentages.

We performed overall group comparisons using Pearson's χ^2 test to assess heterogeneity of distributions across academic disciplines and maturity levels. When expected cell counts were small, Fisher's exact test was applied. For pairwise comparisons between a given discipline and all others, odds ratios (OR) with 95% confidence intervals were calculated.

To evaluate the presence of gradients associated with the maturity score, Likert-scale we dichotomized responses into two categories (disagree=1+2; agree=3+4), an approach commonly recommended when applying trend tests to ordinal data [26,27]. Linear trends were then tested using the Cochran–Armitage trend test. When multiple simultaneous comparisons were conducted, the alpha risk was adjusted using Holm's method. Statistical significance was set at $p < .05$.

Results

Respondent demographics and academic profile

The survey included 388 health professional students. Respondents self-identified as 79% women, 20% men, and 1% preferred not to disclose. Age distribution was: 20–24 years (51%), <20 years (14%), 25–29 years (14%), 30–34 years (6%), and ≥35 years (15%). Students aged 30–34 represented 6%, and those over 34 made up the remaining 15%. In terms of discipline, the largest group of respondents were nursing students (56%), followed by medicine (18%), pharmacy (17%), midwifery (6%) and physiotherapy (3%). Years of study were widely distributed: first- and second-year students together formed nearly half of the respondents (21% and 25% respectively), third year students 20%, fourth year 7%, fifth year 13%, sixth year 3%, and those beyond 11%.

In addition to these demographic and academic characteristics, a composite maturity score was derived from knowledge and self-efficacy items related to GenAI. Just over half of the students (52%) were classified as having moderate maturity (score=3), while about one third (34%) showed limited maturity (score=2). Only a small minority reported high (8%) or minimal maturity (6%). This distribution suggests that most students placed themselves at an intermediate level of familiarity with GenAI, with relatively few at the extremes. Item-level responses added nuance: foundational knowledge was strong, with most students comfortable with digital technologies and aware of the basics of GenAI; applied judgment and practical skills were more uneven, as many assessed reliability in academic contexts but felt less confident in professional practice; attitudes and reflexivity showed the largest gaps, with limited awareness of model limitations and very few students knew where to find reliable training resources Detailed information is available in Multimedia Appendix 2.

Table 1. Descriptive table of responder characteristics

Characteristics	Participants, n=388 (%)
Gender	
Male	76 (19.6)
Female	308 (79.4)
Prefer not to answer	4 (1.0)
Age Y.O.	
< 20	55 (14.2)
20–24	198 (51.0)
25–29	55 (14.2)
30–34	22 (5.7)
> 34	58 (15.0)
Discipline	
Physiotherapy	13 (3.4)
Midwifery	23 (5.9)
Medicine	69 (17.8)
Pharmacy	66 (17.0)
Nursing	217 (55.9)
Year Of Study	
1st year	82 (21.1)
2nd year	97 (25.0)
3rd year	77 (19.9)
4th year	29 (7.5)
5th year	52 (13.4)
6th year	10 (2.6)
Beyond the 6th year	41 (10.6)
GenAI Self-Perceived Maturity	
Minimal (1)	22 (5.7)
Limited (2)	130 (33.5)
Moderate (3)	199 (51.3)
High (4)	29 (7.5)
NA	8 (2.1)

Self-reported uses

GenAI use in clinical placement

Overall, 52.6% of the 388 students reported using GenAI during their clinical placements (Table 2). A global chi-square test comparing the five retained disciplines (Pharmacy, Nursing, Medicine, Physiotherapy, Midwifery) showed that adoption rates are not homogeneous ($\chi^2=10.71$, $p=.03$), indicating that at least one discipline departs from the overall pattern. Post-hoc tests refined this picture. After Holm adjustment for the five simultaneous contrasts: 1. Midwifery stood out with a markedly lower uptake (26.1% vs 50.3% in the rest; $OR=0.30$, 95% CI 0.11–0.77; $p=.049$); 2. Pharmacy showed the highest raw proportion (63.6%), but this higher usage did not reach significance after controlling for multiple comparisons ($OR=1.73$, 95% CI 1.00–2.99; $p=.23$); and 3. Nursing (53.9%), Medicine (47.8%) and Physiotherapy (46.2%) did not differ significantly from the pooled average (all $p>.75$). In short, the significant global heterogeneity is driven almost entirely by lower adoption in Midwifery, while the observed higher rate in Pharmacy did not reach statistical significance after familywise error correction at 5% level.

Adoption was also strongly stratified by self-perceived maturity in GenAI (Table 2). Usage increased continuously in all four categories: from only 9% among students with minimal maturity to 40% in

the limited group, 61% in the moderate group, and 76% in the high group. The association was highly significant in a global chi-square test ($\chi^2=37.3$, $p<.001$) and confirmed by a Cochran–Armitage test for linear trend ($Z=6.01$, $p<.001$). This gradient shows that adoption increased steadily with higher levels of self-perceived maturity.

Table 2. Prevalence of GenAI Use in Clinical Internships (overall (a), by health sector (b), and by self-perceived digital maturity(c)).

(a). Overall prevalence of GenAI use

GenAI Use In Clinical Internships	Yes, n (%)	No, n (%)
Overall	204 (52.6)	184 (47.5)

(b). GenAI use by discipline

Health Sector	Yes, n (%)	No, n (%)	OR vs rest	p-value
Physiotherapy	6 (46.1)	7 (53.9)	0.77	0.78
Midwifery	6 (26.1)	17 (73.9)	0.30	0.049*
Medicine	33 (47.8)	36 (52.2)	0.79	1.00
Pharmacy	42 (63.6)	24 (36.4)	1.73	0.232
Nursing	117 (53.9)	100 (46.1)	1.13	1.00

* Statistically significant after holm-adjustment

(c). GenAI use by self-perceived digital maturity

Maturity Score	Yes, n (%)	No, n (%)	χ^2 Pearson (p)	Cochran-Armitage trend (p)
Minimal (1)	2 (9.1)	20(90.9)		
Limited (2)	52 (40.0)	78 (60.0)	$\chi^2=37.25$	$Z=6.01$
Moderate (3)	122 (61.3)	77 (38.7)	$(p<.001*)$	$(p<.001*)$
High (4)	22 (75.9)	7 (24.1)		

* Statistically significant

Reasons for not adopting GenAI during internship situations

Across the 184 respondents who reported no use of GenAI (table 2), the most frequently cited reasons were that they did not perceive a need for it (32% of all non-users, Table 3), that they felt insufficiently guided on best practices (21%), or that they did not find it relevant to their practice (18%). Fewer students indicated limited familiarity with the tools (10%) or no prior awareness (5%). This was followed by insufficient guidance on best practices (21%) and a lack of interest (18%). Technical unfamiliarity, either not knowing how to operate the tools (10%) or never having heard of them (5%), was less frequently reported, while open-ended “Other” responses accounted for 14%. The pattern shifted when examined by discipline. In physiotherapy (n=7) and midwifery (n=17), reported attitudinal reasons were more frequent: over 60% indicated either limited interest or perceived lack of relevance, while requests for guidance were uncommon. Some physiotherapy students reported concerns that GenAI could hinder the development of personal clinical reasoning. In Medicine (n=36) and Pharmacy (n=24), motivational and competence factors coexisted: roughly one-third of students reported disinterest or irrelevance, and another third pointed to missing guidelines or technical skills. In Nursing (n=100), insufficient knowledge emerged as the primary obstacle: one in four students reported lacking best-practice guidance, and 12% did not know how to

use the tools. Nevertheless, “no need” remained a frequent secondary reason (32%).

Qualitative comments sharpened these contrasts. Some physiotherapy students expressed concerns that GenAI might hinder the development of personal clinical reasoning. Some midwifery students questioned the perceived clinical relevance of the tool and described “digital pollution” as a deterrent. Medical and pharmacy students highlighted environmental concerns, confidentiality risks, doubts about information reliability, and fears of professional judgement for using GenAI. Nursing students most often highlighted risks such as a potential reduction in reflective capacity or depersonalization. Several reported a preference for official protocols or staff advice, and some described GenAI as posing “more threats than benefits.”

Table 3. Reasons for not adopting GenAI during internships among non-user respondents (n=184)

Reason For Non-Use	Overall n (%)	Nursing n (%)	Medicine n (%)	Pharmacy n (%)	Midwifery n (%)	Physio. n (%)
It does not interest me	34 (18.5)	13 (13)	10 (27.8)	3 (12.5)	5 (29.4)	3 (42.9)
I do not need it	59 (32.1)	32 (32)	10 (27.8)	9 (37.5)	6 (35.3)	2 (28.6)
I do not know how to use it	18 (9.8)	12 (12)	4 (11.1)	2 (8.3)	0 (0)	0 (0)
I don't know the best practices for using it	38 (20.7)	25 (25)	7 (19.4)	2 (8.3)	3 (17.6)	1 (14.3)
I was not aware of it	10 (5.4)	6 (6)	0 (0)	3 (12.5)	1 (5.9)	0 (0)
Other	25 (13.6)	12 (12)	5 (13.9)	5 (20.8)	2 (11.8)	1 (14.3)

Self-reported use of GenAI in internship situations

Among the 204 respondents who reported using GenAI (Table 2), usage was primarily for documentation and information retrieval (Table 4). Between 69% and 78% of students used it to translate, write or rephrase texts, retrieve information, or conduct literature search, while only 38% to 55% applied it to clinical tasks such as case simulation, writing patient documents, or preparing patient communications. This trend was confirmed in the frequency of use: a quarter of students (23%–26%) used GenAI every week for documentation tasks, compared to 6%–15% for direct clinical uses. Open-ended responses (free-text comments) added nuance, mentioning other purposes such as clinical reasoning assistance, pedagogical explanation, preparation of learning materials, content synthesis, coding assistance, and formulation of internship objectives.

Table 4. Frequency of GenAI usage by task

Item	Ever used n (%)	At least once a week n (%)
Content translation	145 (71.1)	19 (9.3)
Report / article writing	141 (69.1)	27 (13.2)
Info extraction	159 (77.9)	53 (26.0)

Bibliographic search	152 (74.5)	47 (23.0)
Clinical simulation	112 (54.9)	31 (15.2)
Drafting patient documents	78 (38.2)	13 (6.4)
Preparing patient communication	78 (38.2)	15 (7.4)

Disclosure of sensitive information to GenAI

The survey indicated that most students avoided entering direct patient identifiers into GenAI prompts, yet a sizeable minority reported entering personal or clinical information. (Table 5). Nearly three quarters (74%) reported never sharing a patient's name, identification number, or full address, and only 1.5% reported doing so frequently; however, about 23% acknowledged at least one instance, whether deliberate, experimental, or accidental. Self-disclosure was more common: 43% reported having provided their own name or similar data at least once, and 9% did so routinely. The broadest category of disclosures involved medical content: almost half of the students (47%) submitted anonymized clinical data, and 10% reported doing so regularly.

Table 5. Self-reported disclosure of sensitive information when using GenAI (n=204)

Type of data disclosed	Never n (%)	Once n (%)	A few times n (%)	Often n (%)	Maybe mistakenly n (%)	Don't know n (%)
Patient-identifying data (name, ID, address)	151 (74.0)	12 (5.9)	22 (10.8)	3 (1.5)	11 (5.4)	5 (2.5)
Student's own personal data (name, identifiers)	109 (53.4)	18 (8.8)	39 (19.1)	18 (8.8)	12 (5.9)	8 (3.9)
Real medical data (anonymized or not)	100 (49.0)	17 (8.3)	56 (27.5)	20 (9.8)	3 (1.5)	8 (3.9)

Perceived benefits and risks

Perceived benefits of GenAI use in clinical practice

Students evaluated seven potential benefits of GenAI on a four-point Likert scale, with responses clustering into two tiers across the 388 respondents (Figure 1). Strong majorities agreed or strongly agreed that GenAI could facilitate clinical document drafting (81%, median 3 [3–3]) and improve information accessibility (69%, median 3 [2–3]). Perceptions were positive but more cautious for personalized care-plan creation, diagnostic accuracy, and overall care efficiency: 52%–65% expressed agreement, with a median of 3 [2–3]. By contrast, patient-information collection and prognostic accuracy drew the most divided views, with over half of respondents disagreeing and endorsement falling to 41% and 40%, respectively (median 2 [2–3]). Detailed distribution of responses is provided in Multimedia Appendix 3.

Open-ended responses added nuance to these figures. Several respondents described concrete administrative gains, such as automatic transcription of patient interviews, rephrasing complex sentences, and drafting prescriptions, certificates, or discharge letters. Others pointed to patient-facing advantages, including using GenAI to explain diagnoses in plain language or to generate checklists that help students remember essential examinations. An isolated comment emphasized GenAI's potential as a reflective aid, functioning like a neutral sounding board that surfaces red flags

and supports critical vigilance. Finally, some students envisioned its use to streamline workflows in busy clinical units.

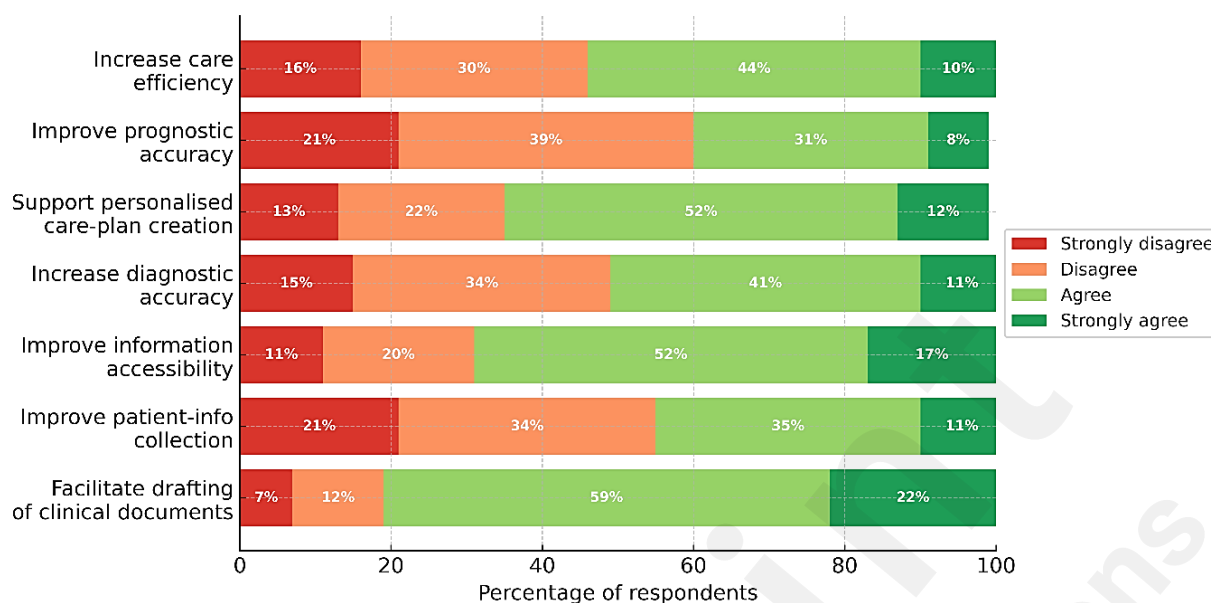


Figure 1. Perceived benefits of GenAI for (n=388)

Perceived risks of GenAI use in clinical practice

Students identified three main risks (Figure 2). Large majorities agreed or strongly agreed that GenAI could create professional dependence (91%), erode clinical skills over time (85%), and heighten the risk of breaching medical confidentiality (87%). Each of these items retained a median of 3 [3–4] on the four-point scale. A smaller majority, 59%, feared that GenAI would challenge professional competencies more broadly. By contrast, most respondents were skeptical that the technology would replace healthcare staff (63% disagreed or strongly disagreed), lengthen training programs (64% disagreed), or exacerbate inequalities of access to care (62% disagreed); these lower-ranked items clustered around a median of 2 [2–3]. Detailed distribution of responses is provided in Multimedia Appendix 4.

Open-ended responses confirmed this hierarchy of concerns. Many echoed the top-rated risks, warning that “total dependence” might “stop us thinking”, that un-sourced outputs would increase liability, and that GenAI could not replace direct clinical examination. Additional nuances also emerged. Several students feared the amplification of existing diagnostic biases and the delivery of “ready-made” answers that could curb individual reflection. Others raised commercial and ethical worries, citing monetization of health data and unequal access to paid versions. A few pointed to downstream risks such as patient self-medication based on GenAI advice or reduced social interaction with patients and peers. Across these comments, a consistent refrain persisted: robust human knowledge, critical appraisal, and peer consultation remain indispensable safeguards.

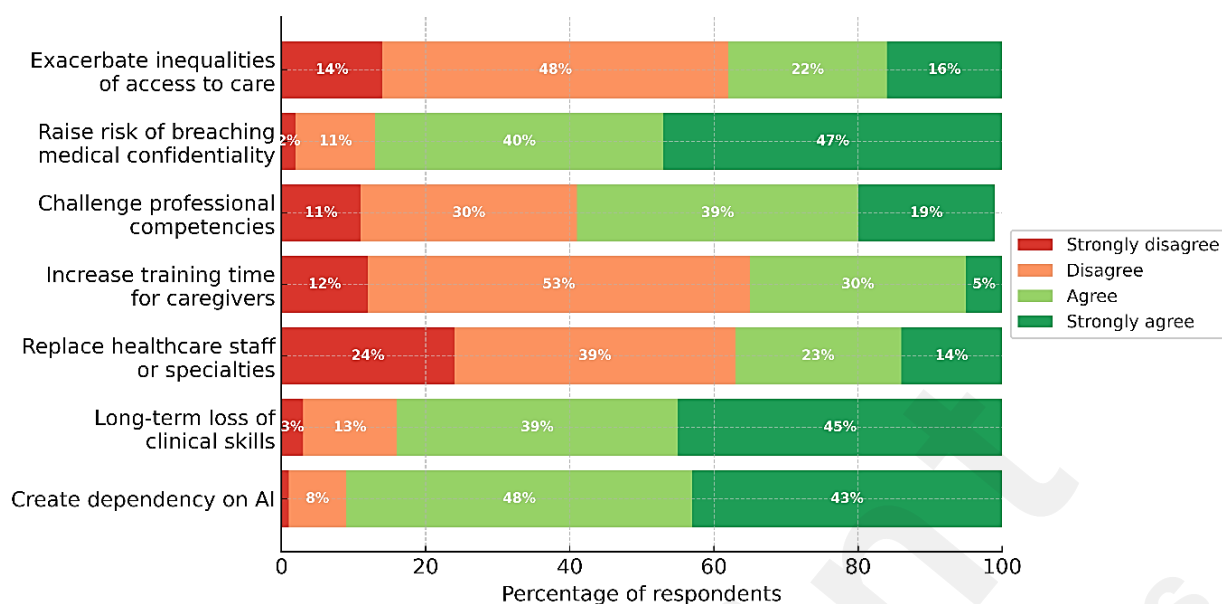


Figure 2. Perceived risks of clinical use of GenAI (n=388)

Training and Support Needs for GenAI Use

Across the seven items on training and support, the median response was “Agree” for every statement (Figure 3). Four needs gathered the strongest endorsement: ethics and regulatory awareness training (78% “Agree” or “Strongly agree,” median 3 [3–4]), a best-practice clinical guide (78%, median 3 [3–4]), personalized coaching tailored to each health profession (74%, median 3 [3–4]), and training in human–AI collaboration (73%, median 3 [3–4]). Practical workshops (65%, median 3 [2–3]) and theoretical courses (63%, median 3 [2–3]) also attracted solid support, while a self-learning platform secured 62% agreement (median 3 [2–3]). Active disagreement ranged from 22% for ethics training to 37% for theoretical courses with “Strongly disagree” never exceeded 11%. Open-ended responses provided further context. Several students stressed the need for clear ethical and legal boundaries, specifying when use is permitted, who owns the output, and how to protect confidential data, and called for guidance that is profession-specific and regularly updated. Others emphasized the importance of in-person workshops and locally hosted open-source tools, citing cost and privacy concerns. Several highlighted the need for curated, trustworthy resources, noting that piecemeal web searches are unreliable. Gaps in foundational digital skills also surfaced, alongside a desire for mentorship that encourages critical reflection. Finally, a few respondents urged that training should address the environmental footprint of largescale GenAI systems. Detailed distribution of responses is provided in Multimedia Appendix 5.

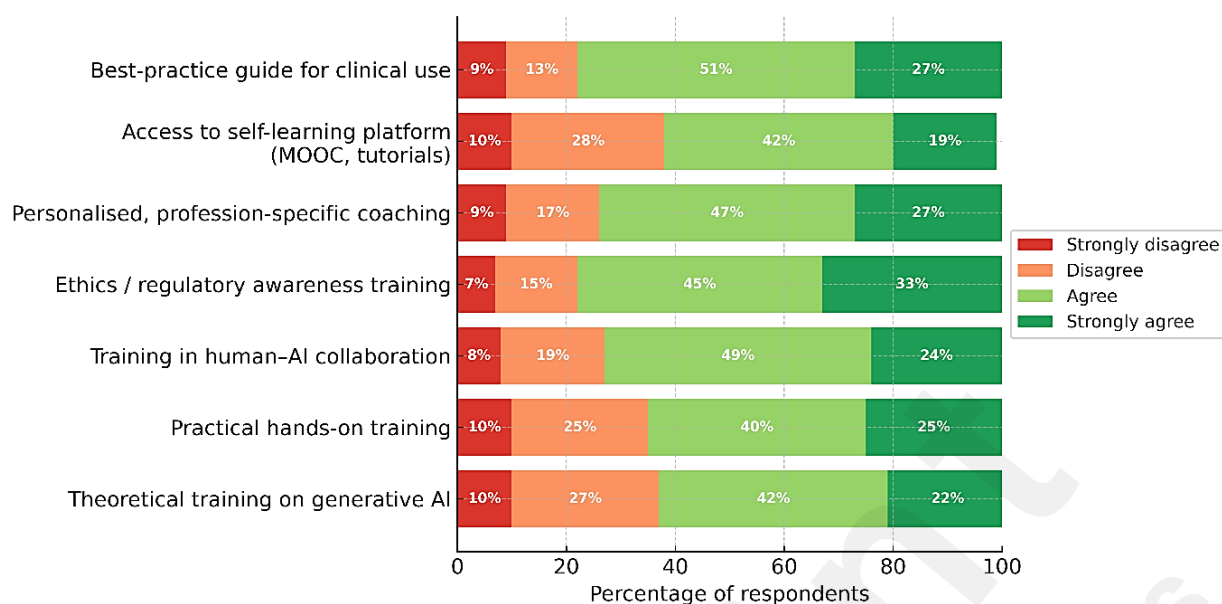


Figure 3. Training and supports needs for GenAI (n=388)

Governance & organizational readiness

Beyond individual practices and training needs, seven items related to organizational readiness and governance were examined to capture how students perceived the institutional context in which GenAI is, or is not, framed during internships. Across the seven items on governance and organizational readiness (Figure 4), students reported limited institutional communication and safeguards. Fewer than 15% recalled supervisors providing information on legal responsibilities (14%) or conditions of GenAI use during placements (15%), with median ratings at the lowest category [1–2]. Regulation was likewise perceived as insufficient, with only 10% agreeing that current frameworks were adequate (median 2 [1–2]). Ethical compliance was judged more ambivalently: 38% agreed that GenAI use respected ethical principles, while 62% disagreed (median 2 [2–3]). Operational safeguards received the poorest scores, as fewer than 5% believed staff were trained for clinical use and only 16% considered that tool biases were accounted for. By contrast, transparency toward patients emerged as the single domain of strong consensus: three-quarters of respondents (75%) agreed that patients ought to be informed when GenAI was used in their care (median 3 [2–4]). Detailed distribution of responses is provided in Multimedia Appendix 6.

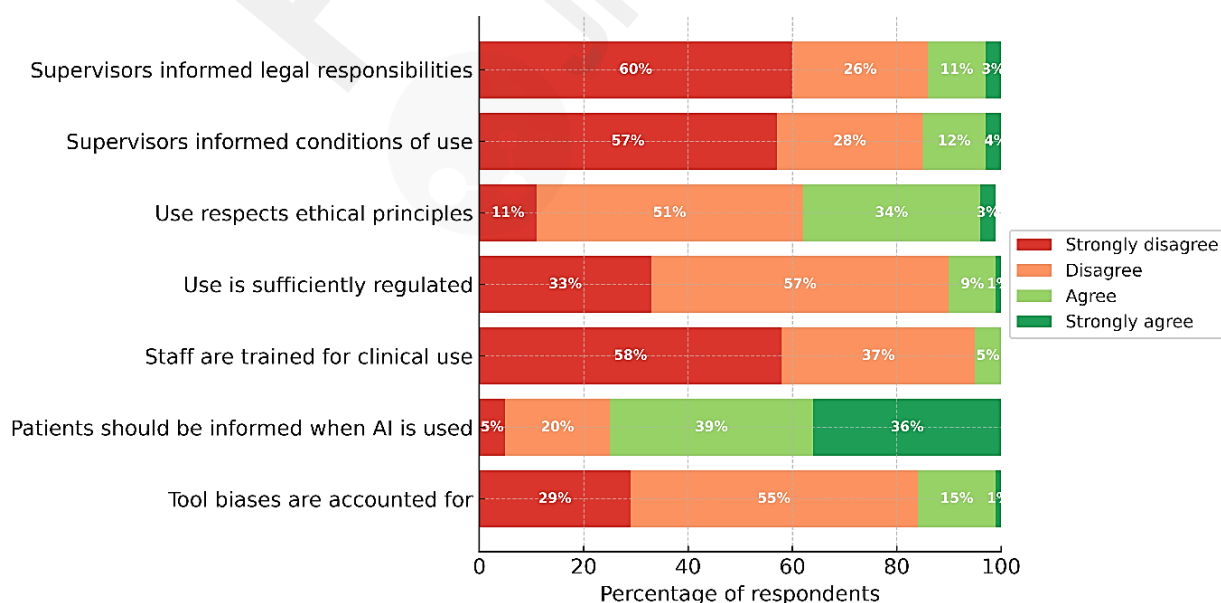


Figure 4. Governance and organizational readiness (n=388)**Discussion**

This survey of 388 health professional students offers novel insights into how generative artificial intelligence is perceived and mobilized during clinical placements in France. The discussion is structured around three main dimensions: the observed patterns of adoption, their resonance with educational processes such as competency acquisition and professional identity formation, and the broader ethical and institutional challenges raised by these findings. The results revealed clear trends, but also tensions, particularly in relation to the educational dimensions of progressive competency acquisition, professional identity formation, and the role of reflexivity. Wald describes professional identity formation as a central goal of medical education, understood as a developmental and transformative process nurtured by guided reflection, and supportive relationships and mentorship [28].

The investigation of self-perceived maturity about GenAI was undertaken to position students along this developmental continuum and to clarify their support needs. Most students reported an intermediate level of maturity, reflecting basic familiarity but limited confidence in using GenAI autonomously. This uneven self-efficacy, already noted in other international contexts, underscores the importance of structured guidance: in line with competency-based education frameworks, students' confidence develops through exposure and supervision but remains fragile without clear benchmarks. This aligns with Suárez-García et al., who, in a pre-post intervention study among undergraduate medical students in their clinical phase, demonstrated that students with higher digital self-efficacy benefit more from GenAI-mediated educational interventions, confirming the central role of this variable in learning [29]. However, while their study emphasized individual learner profiles, the present findings suggest that students' self-perceived efficacy often reflects the absence of pedagogical frameworks that would help objectify and structure these competencies.

Balancing efficiency and reflection: GenAI in clinical learning

Students declared uses of GenAI were concentrated on documentary and informational tasks, positioning it primarily as a cognitive and organizational support. This aligns with the view of technology as a facilitator of information management and research processes. Monzon and Hays highlighted that GenAI fosters autonomous learning, strengthens cognitive engagement, and supports efficient retrieval practices, underscoring its role as a structural aid to learning [30]. However, medical documentation is also a critical space for cultivating clinical reasoning and professional responsibility. Automating this dimension without explicit pedagogical framing risks narrowing opportunities for reflexivity and the practice of clinical rigor. Mentions of direct use for reasoning support, though a minority in this survey, remain significant: because clinical reasoning is a foundational competency, premature delegation to GenAI could compromise the development of autonomy and judgment. This concern resonates with debates about the "hidden curriculum", the implicit socialization process shaping professional identity beyond formal teaching, and about the balance between efficiency and reflective learning [31]. Recent works, such as the MedSimAI clinical simulation platform, demonstrate that when embedded in an educational framework with structured feedback and validated assessment rubrics, GenAI can enrich clinical reflection and support autonomous practice [32]. Yet without explicit curricular integration, health professional students' engagement with GenAI risks remaining superficial and overly dependent on system outputs. This creates vulnerability to automation bias, a tendency described in the literature on clinical decision support systems, where over-reliance on technology may erode critical vigilance and compromise patient safety [33].

Choice not to use GenAI as reflection: interpreting students' reservations

The reasons for non-use added further nuance: far from reflecting simple unfamiliarity, they often reflected deliberate choices and meaningful concerns, including lack of clinical relevance, fear of

diminished reflexivity, confidentiality risks, and environmental impact. These reservations echo the findings of Tortella et al. [6], who reported that in Italy more than half of physiotherapy students avoided chatbots for academic purposes and only 10% used them during placements. Their reluctance was not mainly due to ignorance but to fears of inexactitude and error, and to perceptions of limits in managing complex tasks. For educators, such reservations should not be seen as resistance to technology but as a pedagogical resource, calling for explicit and shared frameworks that help students exercise critical judgment, whether they ultimately adopt the tool or not.

Perceived benefits: from documentation relief to clinical boundaries

Perceived benefits extended beyond declared uses but remained distinct from reasons for non-use. Consensus centered on documentary value and information access, confirming that GenAI is primarily viewed as a cognitive and organizational facilitator. Perceptions became more nuanced regarding personalized planning, diagnostic reasoning support, or efficiency gains: students acknowledged potential but withheld full trust. This caution aligns with Janumpally et al., who observed that while GenAI can enhance the learning organization and support aspects of clinical reasoning, its contribution depends on the reliability of outputs and cannot substitute for human judgment [34]. Benefits were most debated in the context of clinical data collection and prognostication, domains perceived as sensitive because they directly implicate the care relationship and professional responsibility. Janumpally et al. likewise emphasized risks of inaccuracy, bias, and confidentiality breaches associated in these areas, which helped explain students' persistent reluctance. Overall, perceived benefits did not reflect uniform endorsement but rather a spectrum: strong enthusiasm for documentation relief, cautious interest in selected cognitive functions, and rejection when tasks touched the core of professional identity.

Perceived risks: dependence, skill erosion, and confidentiality

Health professional students perceived risks centered on three main concerns: dependence on the tool, erosion of clinical skills, and breaches of confidentiality. Additional worries included diagnostic bias, uncertainty about legal responsibility, and the substitution of critical reflection by ready-made answers. Other issues, such as the monetization of health data and the environmental impact of large GenAI models, were seen as risks at the intersection of clinical practice and broader societal challenges. These perceptions resonate with the concept of over-reliance described in the literature on clinical decision support systems, and with the notion of dependence on "assistive AI", the lowest degree of autonomy where the system supports but does not replace human judgment, as discussed by Abdelwanis et al. [33]. They also extend findings from other student contexts in which concerns of result inaccuracy and confidentiality had already emerged as major barriers [6]. Taken together, the findings suggest that students in this study did not primarily report fears of being replaced by technology; instead, many expressed concerns about a more subtle displacement, including dilution of judgment, weakening of professional accountability, and reduced human interaction in clinical practice.

Beyond literacy: approaching ethical and patient-centered GenAI education

Students' training needs extended well beyond technical mastery. They encompassed the full educational triad of knowledge, skills, and professional attitudes: knowledge of ethical and regulatory frameworks; practical competencies developed through workshops and profession-specific coaching; and professional attitudes cultivated through mentorship, reflexivity, and attention to sustainability. These expectations align with recent calls to design health AI curricula that move past technical literacy to incorporate critical thinking, ethics, and patient-centered judgment. Komasa and Yokohira emphasized this shift, showing how the rise of GenAI compels a rethinking of traditional medical professionalism [35]. Their proposed framework integrates technological fluency with enduring humanistic values such as empathy, integrity, and accountability, to prepare future clinicians for a responsible, ethical, and patient-centered use of GenAI.

Toward an enabling framework: integrating governance and training for GenAI

Findings on governance and organizational readiness revealed an institutional vacuum: limited communication from supervisors, minimal staff training, and insufficient attention to bias or regulation. This absence of reference points reflects both the risks identified (dependence, skill erosion, confidentiality) and the needs expressed (ethics, best-practice frameworks, mentorship). In this context, students navigate GenAI without genuine guidance or safeguards, yet consistently emphasize the importance of transparency, particularly toward patients. Governance and training should not mandate adoption but instead foster the reflective judgment needed to determine GenAI's appropriate role in clinical learning. Governance should be conceived as an enabling framework, paired with structured training, explicit objectives, updated recommendations, and clearly defined competencies. Crucially, this also requires targeted training and the regular reinforcement of established professional standards on confidentiality and clinical practice, ensuring that ethical safeguards are not only taught but actively maintained. Such alignment between governance and pedagogy would help guard against superficial or unreflective engagements and embed GenAI within an educational process that values discernment, autonomy, and professional responsibility.

Evolving learning approaches: embedding GenAI in clinical curricula

Taken together, these results call for curricula that move beyond fragmented, discipline-specific approaches. The expectations expressed by students, combined with the risks identified and the absence of clear governance, argue for the creation of a transversal common core, independent of medical or paramedical tracks, that lays the foundations for a critical and responsible approach of GenAI. These foundations should integrate ethical, regulatory, and technical knowledge; practical skills developed through guided practice, workshops, and clinical simulation; and professional attitudes such as reflexivity, autonomy, and professional accountability. Such a framework cannot be limited to theoretical instruction: it requires innovative pedagogies that immerse students in experimentation, critical reflection, and identity formation. Recent initiatives such as MedSimAI (Hicke et al., 2025) illustrate this potential: by embedding GenAI in clinical scenarios with structured feedback and validated assessment grids, they demonstrated that practical skills, clinical reasoning, and professional autonomy can be developed simultaneously. Approaches of this kind provide a model for transforming spontaneous, superficial use of GenAI into integrated, conscious, and patient-centered competencies.

Limitations

This study has several limitations that should be acknowledged. First, it was conducted within a single French university, which might a priori limit the international generalizability of the findings, although this institution is among the largest provincial universities in France. However, the trends observed here are remarkably consistent with those reported in the international survey by Busch et al., which included 4,596 students from 192 faculties across 48 countries and highlighted a global deficit in formal AI education despite the rapid penetration of generative tools into student practices [36]. Second, data on usage was based exclusively on students' self-reports, which prevents objective verification of actual practices or the identification of possible informal supervisory frameworks. This limitation, however, should be nuanced: our intention was not to measure actual behaviors but rather to document practices and representations as they are lived and perceived by students. In a context where no pedagogical framework is yet established, such perceptions largely shape the appropriation of GenAI and thus constitute a central result in themselves, in line with the conclusions of Busch et al. [36]. Third, no data were collected from clinical supervisors or educational leaders, which prevents us from affirming with certainty the absence of any institutional framework. This was an intentional methodological choice, as our focus was to capture the student experience. Yet this limitation also highlights a central point: for the first time in recent medical education, it may be the case that supervisors do not hold greater expertise than their students with respect to GenAI. The lack

of a formal framework may therefore not simply reflect insufficient communication but rather a situation in which teachers and learners are simultaneously discovering an emerging tool, as recently suggested by Blanco et al. or McCoy et al. [37,38]. Finally, interprofessional heterogeneity represents another limitation: some health professions were underrepresented, which limited the possibility of robust profession-specific analyses. This limitation reflects our primary aim, which was to provide a global mapping of student practices during clinical placements rather than to compare individual healthcare disciplines. Moreover, the rapid diffusion of GenAI appears to homogenize students' relationship with the tool, and our results show that, except for midwifery, where non-use was significantly higher, most disciplines behaved similarly. Nevertheless, the absence of profession-specific analyses constitutes a limitation, especially since recent studies have demonstrated that attitudes and AI literacy may vary substantially across healthcare disciplines [39,40].

Perspectives

Looking ahead, several directions appear essential. Future research should move beyond single institutions to include multicentric and international comparisons, thereby enabling the identification of contextual variations and common challenges. Longitudinal approaches will also be required to capture how perceptions, competencies, and professional identities evolve as GenAI becomes increasingly embedded in health professions education. Finally, triangulating student perspectives with those of supervisors, educators, and institutional leaders will be crucial for developing evidence-based strategies that responsibly integrate GenAI into curricula, while respecting the distinctive needs of different health professions.

Conclusion

In conclusion, this study highlights both the opportunities and the risks associated with the spontaneous adoption of GenAI by health professional students during clinical placements. While students primarily mobilized GenAI as cognitive and organizational aid, their perceptions revealed significant concerns about dependence, erosion of skills, and confidentiality, alongside a strong demand for structured guidance. These findings call for curricular innovations that foster reflexivity, autonomy, and professional responsibility, while embedding GenAI into ethically grounded and supervised learning experiences. At the same time, they underscore the urgent need for explicit pedagogical and professional frameworks, echoing calls already raised across higher education. McDonald showed that leading U.S. universities are already developing institutional policies to regulate GenAI [13], García-López et al. emphasized the ethical and regulatory urgency of such frameworks [41], and Symeou et al. demonstrated a methodological pathway for constructing evidence-based interdisciplinary guidelines, providing a model for responsible implementation [42].

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During the preparation of this manuscript, the authors used ChatGPT (OpenAI, GPT-5, 2025) for code optimization in data analysis and for language editing. The authors reviewed and edited all outputs and take full responsibility for the content, data interpretations, and conclusions of this publication.

Availability of data and materials

The data supporting the findings of this study are not publicly available due to ethical and privacy restrictions. Anonymized datasets can be made available from the corresponding author, SK, upon reasonable request and subject to approval by the institutional ethics committee.

Conflict of interest

The authors declare no conflict of interest.

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Authors' contributions

SK conceived and coordinated the study and drafted the initial version of the manuscript. CMT and KG contributed to methodological development. Analyses were performed by SK, CMT, and MM. Data collection was carried out by SK, KG, and MM. Interpretation of the results was conducted by SK, CMT, KG, and MM. NV provided overall supervision and critical guidance throughout the project. All authors critically reviewed the manuscript and approved the final version.

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Supplementary Files

Multimedia Appendixes

Full questionnaire items in French with English translation.

URL: <http://asset.jmir.pub/assets/65d9b9bd38bfc6cb9d36c0db9c56735f.docx>

Self-reported maturity regarding GenAI (NA excluded).

URL: <http://asset.jmir.pub/assets/928b20697af900e97575bf3a4d8645ba.docx>

Perceived benefits of GenAI in clinical practice.

URL: <http://asset.jmir.pub/assets/b78ca19714e7d32d7923a0b188f3ed9e.docx>

Perceived risks of clinical use of GenAI.

URL: <http://asset.jmir.pub/assets/d6873fbe89c610ea3d54ed704feb91e9.docx>

Stated training and support needs for GenAI use.

URL: <http://asset.jmir.pub/assets/a6589f1869ef75f68e3faede6e5b575e.docx>

Governance and organizational readiness.

URL: <http://asset.jmir.pub/assets/48673280b738192e4496711ed9a3ec84.docx>