

Article

How Medical Students Use and Perceive Generative Artificial Intelligence for Learning and Assessment: A Cross-Sectional Study at a Regional Australian Medical School

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Abstract

Generative artificial intelligence has been rapidly adopted by university students, yet there is limited evidence describing how and why medical students use it, particularly in regional settings. This cross-sectional study examined the use of generative artificial intelligence for learning and assessment among medical students at James Cook University, a regional Australian medical school with three North Queensland campuses. All enrolled students (Years 1–6) were invited to complete a 24-item online survey; closed-ended items were analysed using frequency and bivariate analyses by year level and gender, with correction for multiple comparisons, and open-ended responses were analysed using qualitative content analysis. In total, 438 students responded. Eighty percent reported using artificial intelligence for their studies or assignments, and 95% supported its use in medical education in some capacity. The most common uses were explaining concepts (56%) and answering medical content questions (54%). Pre-clinical students reported greater study-related use, whereas clinical year students reported greater assessment-related use. Male students also reported higher levels of use, willingness to pay, and trust in AI tools. Although uptake was high, trust was moderate, and students expressed concerns about professionalism and critical thinking. Medical schools should provide explicit guidance on acceptable use, incorporate artificial intelligence literacy training and ethical use guidelines, and redesign assessment to protect the skills students perceive to be most at risk.

Keywords: artificial intelligence; generative artificial intelligence; medical education; medical students; cross-sectional study; learning; assessment; academic integrity; critical thinking



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1. Introduction

University students face complex challenges including high academic workloads, financial pressures and often significant stress, depression and burnout [1]. This is especially true for medical students, who have amongst the highest workloads [1,2]. Medical students must balance high contact hours in clinical placements and tutorials with self-directed study on difficult subjects, alongside high assessment density and competency requirements [2]. Concepts must be understood and integrated across basic sciences, anatomy and pathology, with learning stresses often further exacerbated by a competitive culture between students and reluctance to seek help [3]. In addition, international-origin students who comprise a significant proportion of many medical student cohorts also experience some degree of homesickness and cultural adjustment [4]. Globally, up to one in three medical students

report symptoms of anxiety and burnout [5]. It is not surprising, then, that undertaking a medical course has been described as not a race but a ‘marathon’ over many years.

Given these pressures, it is no surprise that medical students are increasingly turning to artificial intelligence (AI) for learning and assessment [6]. AI refers to computational algorithms that allow systems to process data, identify patterns and make decisions in ways that resemble human intelligence [7,8]. The recent arrival of low-cost, accessible applications such as ChatGPT has driven a surge in AI use among medical and other university students [6–8]. These tools are built on underlying technologies including machine learning (ML), natural language processing (NLP) and generative pre-trained transformers (GPTs).

This study examines how medical students at James Cook University (JCU), a regional Australian medical school, engage with and perceive generative AI in their learning and assessment. The study addresses three research questions: (1) how, and how extensively, do medical students use generative AI for learning and assessment; (2) do usage patterns and attitudes differ by year level and gender; and (3) what benefits and risks do students perceive in its use? The contribution of the study is twofold: it provides one of the largest Australian datasets on medical student AI use, spanning all six year levels of a medical degree, and to our knowledge, it is the first such study conducted in a regional Australian setting, where students often experience different social and demographic circumstances to their urban counterparts [9–12]. The study therefore examines patterns of AI uptake and their potential association with regional location while acknowledging the limitation that, in the absence of a metropolitan comparison group, a true association cannot be established. As a cross-sectional, self-report survey, the study describes patterns of use, perceptions and associations; it does not, and cannot, test causal effects of AI use on learning or performance.

2. Related Research

2.1. Artificial Intelligence in Medical Education

Large systematic reviews have recently documented this uptake. Gordon et al. describe how AI has become ubiquitous in learning, assessment and the automation of case logs [6], with adoption strongest among clinical-year medical students [13]. AI is now used on both sides of assessment. Educators use it to generate multiple-choice questions and streamline assessment development, while students use it to create practice questions for self-testing. This replaces considerable human effort, although human verification is still needed to ensure question quality [14–16]. Across the studies included, ChatGPT emerged as the preferred tool.

Gordon and colleagues have also reviewed perspectives on the ethical implications of AI in medical education [6]. Most medical students and doctors acknowledged its potential benefits. At the same time, they pointed to drawbacks, including weakened doctor–patient relationships and limitations in unexpected or urgent scenarios. So, while AI promises personalised learning, greater efficiency and adaptive teaching, we still lack a clear understanding of how medical students actually use it and how they weigh its advantages and disadvantages.

2.2. Reported Benefits and Risks

The literature attributes several benefits to generative AI in health professional education. These include continuous availability at low cost, personalised and adaptive explanation, support for summarising and synthesis, and automation of low-value tasks [6,7,11–13]. Against these benefits, a growing body of work identifies potential risks. Studies of ‘cognitive offloading’ suggest that delegating synthesis and recall to external tools may weaken the effortful engagement needed for long-term retention and critical thinking [17–20]. Re-

searchers have also described a ‘competence paradox’, where fluency with AI outputs can be mistaken for genuine understanding [21]. Accuracy is a further concern. Large language models can produce incorrect or fabricated (‘hallucinated’) content [22]. Experimental studies show that incorrect AI-generated information can reduce diagnostic accuracy in both medical students [23] and clinicians [24], and performance in healthcare-related decisions remains inconsistent [25]. In response, ethical frameworks for AI use in health professions education emphasise transparency, verification and the protection of academic integrity [26,27].

2.3. Individual Differences in Adoption

Patterns of adoption differ across learner groups. Prior experience and habit shape technology use [28,29], and students exposed to AI earlier in their academic careers report higher usage [30]. Gender differences have been reported consistently. A systematic review of AI use in higher education found that male students report greater usage frequency, familiarity and perceived usefulness than female students [31]. This echoes population studies in which females hold less positive attitudes towards AI, express more concern about its implications and report higher ‘AI anxiety’ [32–34]. A meta-analysis has also found greater risk propensity among males [35]. Theory helps explain these patterns. The Technology Acceptance Model (TAM) proposes that adoption is driven by perceived usefulness and perceived ease of use [36]—two qualities that generative AI platforms clearly exemplify. Consistent with this, recent cross-sectional studies of medical students report high uptake, though alongside concerns about critical thinking and academic integrity [37].

3. Problem Statement

Generative AI has spread among medical students faster than curricula, assessment policies and ethical guidance have adapted. Medical schools currently lack detailed, cohort-wide evidence on three fronts: how students actually use these tools, how use varies across training stages and demographic groups, and what students themselves see as the benefits and risks. Without this evidence, institutional responses risk missing the mark in either direction—unnecessarily prohibitive or insufficiently protective of the cognitive and professional skills medical training exists to develop. This study addresses that gap for one complete medical school cohort.

4. Materials and Methods

4.1. Study Design and Participants

This cross-sectional study was conducted in 2025 at James Cook University (JCU), located in Queensland, Australia. The JCU College of Medicine provides a 6-year Bachelor of Medicine and Bachelor of Surgery (MBBS) degree that consists of 3 years of pre-clinical (basic sciences) medicine (Years 1–3), followed by 3 years of clinical medicine (Years 4–6). The pre-clinical curriculum entails basic science for the foundation of medicine, delivered through lectures and interactive guided learning sessions that include small group and whole class discussions, as well as 1:1 interaction with lecturers and tutors. The clinical curriculum primarily focuses on hands-on clinical-based learning in healthcare settings such as hospitals and clinics, accompanied by lectures, often in small groups, delivered by practising clinicians.

All enrolled medical students at JCU from years 1 to 6 (total population size of 1192 students), based in Townsville, Cairns, and Mackay campuses across North Queensland, were invited to participate in an anonymous online survey study distributed via JCU email lists.

4.2. Survey Instrument and Pilot

The 24-item survey instrument was newly developed by the research team for this study, informed by the published literature on AI use in medical education [6,7,11,13]. It comprised 22 closed-ended questions and two open-ended questions. The survey covered the frequency and duration of AI use; the study and assessment tasks for which AI was used; students' perceptions of its impact on learning and performance; their attitudes towards AI in medical education; and their level of trust in AI outputs. Closed-ended items used yes/no responses, single-choice categorical options, four-point frequency matrices (never/sometimes/often/always) and 0–100 rating scales. References in this article to “regular use” of AI correspond to an affirmative response to the item “Do you use AI for your medical studies or assignments?”; this level of self-reported uptake is consistent with that observed in comparable surveys of medical students [38]. The complete instrument is provided in Supplementary Material File S1.

A pilot study was conducted with 22 MBBS students across Years 2–6 to assess study viability and validity. Pilot participants evaluated the draft survey for likely participation, appropriateness of survey length, clarity and relevance of questions, and potential additional questions. Based on pilot feedback, several items were reworded because pilot participants found them unclear or confusing; items that sounded similar were merged; and items were revised to increase their relevance to JCU medical students by aligning them with the JCU medicine assessment formats and semester assignments. Pilot responses were not included in the final dataset.

4.3. Data Collection

The survey was administered online via SurveyMonkey (SurveyMonkey Inc., San Mateo, CA, USA) during March–August 2025. Information about the study was provided to all JCU MBBS students via an initial email. Students received the survey one week later at the start of an in-person lecture. The email information outlined the study context and rationale, the authors and study population, the conditions of participation, that participation was entirely voluntary, that no identifying personal information would be collected, that teaching faculty would not have access to individual responses, and that all data would be analysed by student members of the research team and reported only as collated summary findings to ensure no individual responses could be identified. For the in-person information, the two student authors presented the study during mandatory lectures across all year levels at the main two campuses (E.J.—Townsville, O.M.—Cairns) to reiterate the information provided in the email and promote the study to maximise participation. Year 1 students were surveyed in the same way but during the second half of their academic year, as the start of the year, before any substantial assessments had been completed, was considered too early for them to have developed stable study habits.

Across all year levels, two reminder emails were distributed over a three-week period, supplemented by social media posts. To enhance participation, students were offered entry into a draw to win one of 115 coffee vouchers, a non-commercial incentive provided by the Northern Queensland Regional Training Hub.

4.4. Data Analysis

Analyses involved: (1) frequency analysis of the closed-ended questions to describe the sample and overall usage and attitudes; (2) bivariate analysis to test for differences by year level (basic science Years 1–3 versus clinical Years 4–6) and gender (female versus male) (Table 1); and (3) qualitative content analysis of the two open-ended questions (Tables 2 and 3). Categorical items were compared using Pearson chi-square tests of independence; 0–100 scale items were compared using independent-samples *t*-tests. All tests

were two-tailed with $\alpha = 0.05$. Given the number of exploratory comparisons, Benjamini–Hochberg false-discovery-rate correction was applied across the categorical comparisons within each factor, and results that did not remain significant after correction are interpreted cautiously. A complete-case approach was used: item-level denominators vary because not all respondents answered every item, and denominators are reported per item. Four respondents did not report their gender as female or male (three did not answer the item, and one preferred not to answer) and were excluded from gender comparisons ($n = 434$).

Table 1. Bivariate analyses of artificial intelligence use and attitudes by year level (basic science Years 1–3 versus clinical Years 4–6) and gender (female versus male). Values are n (%) unless otherwise indicated.

Variable	n	Years 1–3	Years 4–6	p †	Female	Male	p ‡
I use artificial intelligence outside of my medical studies	435	166 (69%)	147 (75%)	0.151	199 (69%)	112 (77%)	0.075
I use artificial intelligence for my medical studies or assignments	436	191 (80%)	157 (80%)	0.893	229 (80%)	117 (80%)	0.879
Duration of use (<6/6–12/>12 months)	400	89/65/67	58/57/64	0.112	111/88/68	35/34/63	<0.001 *
I pay for the program I use	407	30 (13%)	17 (9%)	0.210	21 (8%)	26 (19%)	<0.001 *
Summarising notes/lectures (often/always)	409	98 (44%)	60 (33%)	0.026	100 (37%)	58 (42%)	0.341
Objective structured clinical examination/Multi Station Assessment Task practice (often/always)	409	59 (26%)	66 (36%)	0.034	71 (27%)	54 (39%)	0.009 *
Practising examination-style questions (often/always)	409	95 (42%)	64 (35%)	0.126	97 (36%)	62 (45%)	0.073
Asking medical content questions (often/always)	409	139 (62%)	88 (48%)	0.007 *	141 (52%)	86 (62%)	0.052
Explaining concepts (often/always)	409	151 (67%)	86 (47%)	<0.001 *	153 (57%)	84 (61%)	0.416
Asking questions otherwise directed to lecturers/doctors (often/always)	409	121 (54%)	71 (39%)	0.003 *	117 (43%)	75 (54%)	0.035
Professionalism assignments (often/always)	409	74 (33%)	73 (40%)	0.134	87 (32%)	60 (44%)	0.025 *
Scientific writing (often/always)	409	38 (17%)	24 (13%)	0.291	33 (12%)	29 (21%)	0.018 *
Patient case reports (often/always)	409	23 (10%)	35 (19%)	0.010 *	29 (11%)	29 (21%)	0.004 *
Case logs (often/always)	409	18 (8%)	38 (21%)	<0.001 *	27 (10%)	29 (21%)	0.002 *
Use should be allowed for both study and assignments (vs. study only)	384	114 (57%)	110 (68%)	0.029	138 (56%)	86 (74%)	0.002 *
Proportion of assignments assisted by artificial intelligence (0–100)	378	29.6	30.3	0.815	27.2	35.5	0.004
Proportion of study/examination preparation assisted (0–100)	391	47.6	39.0	0.003	42.4	46.3	0.219
Perceived effect on assignment quality without access (0–100)	350	23.8	22.8	0.694	22.1	25.6	0.196
Perceived effect on study quality without access (0–100)	375	38.3	29.1	0.002	33.1	35.9	0.361
Perceived effect on learning efficiency without access (0–100)	384	48.5	43.7	0.126	46.3	46.2	0.978
Perceived effect on examination grades without access (0–100)	352	27.7	19.8	0.003	24.4	23.7	0.794
Perceived trustworthiness (0–100)	378	45.9	45.0	0.720	41.6	53.3	<0.001

Table 1. Cont.

Variable	<i>n</i>	Years 1–3	Years 4–6	<i>p</i> †	Female	Male	<i>p</i> ‡
Belief it will be detrimental to core values/professionalism (0–100)	371	42.0	40.2	0.522	42.2	39.5	0.365
Belief it will lead to loss of human critical thinking (0–100)	375	61.1	59.2	0.493	60.9	58.9	0.512

† chi-square test (categorical items) or *t*-test (0–100 items), Years 1–3 versus Years 4–6; ‡ female versus male (gender analyses exclude four respondents who did not report gender as female or male). *n* = number of respondents answering the item. Values are *n* (%) for categorical items and means for 0–100 items. * Remains significant after Benjamini–Hochberg false-discovery-rate correction across the 15 categorical comparisons within the factor. Item-level denominators vary owing to item non-response; percentages are based on respondents answering each item.

Table 2. Content analysis of the perceived advantages/benefits of using artificial intelligence in medical studies (*n* = 320).

Theme	<i>n</i> (%)	Representative Responses
Efficiency/time savings	166 (52%)	“makes everything more efficient. . . students can spend more time learning whilst AI handles the organisational work” “Saves time—don’t have to spend ages trying to figure out an answer from 7 websites and textbooks” “Less time spent studying and being able to streamline study”
Explains/simplifies difficult concepts	103 (32%)	“break complex concepts into simple terms making it easier for students to learn and understand” “if you don’t understand something it can re-explain in many ways” “Explains things in ways lecturers/others cant”
Summarising notes, lectures and literature	62 (19%)	“Rapidly summarizes large volumes of medical literature” “Summarising lecture slides” “collecting information in one place rather than having to read through a massive number of journal articles”
Generating practice questions/self-testing	52 (16%)	“generate unlimited amount of practice questions related to the content” “Easier to study for exams as can have it test your knowledge” “create question banks without already knowing the answer or spending a lot of time arranging them”
Assignment support (structure, editing, grammar)	48 (15%)	“assisting with structure—spelling/grammar checks” “rewording paragraphs already written” “structuring and developing arguments for assignments”
Quick access to information/answers	35 (11%)	“comprehensive and instant information, which is accessible” “can answer questions that google doesn’t answer as easily”
Clinical/OSCE/case practice	26 (8%)	“creates practice cases for clinical skills/history taking” “good to act as a fake patient in an osce scenario” “generate very detailed patient details with history and examination findings—useful for OSCE practice with friends”
Idea generation/brainstorming	24 (8%)	“display ideas that you wouldn’t have thought about” “Helps with brainstorming” “come up with topics for assignments”
Automates tedious/low-value tasks	23 (7%)	“Can do mundane tasks for you, such as writing case logs or notes” “saves time on useless assignments like PEALs” “time-consuming tasks that don’t really help your learning”

Table 2. Cont.

Theme	n (%)	Representative Responses
Availability/not reliant on staff	20 (6%)	"Help when lecturers not accessible. . . after hours" "Weekend access to a lecturer" "Saves having to ask or email tutors or lecturers"
Personalised/adaptive learning	16 (5%)	"Customised information that can suit individual students" "can frame answers in way that is easier to understand and tailored to you" "more personalised way of learning"

Themes mentioned by $\geq 5\%$ of respondents, ranked by frequency. Responses could be coded to more than one theme, so percentages sum to more than 100%. Two to three representative responses are shown per theme to illustrate its range. Other benefits each mentioned by $<5\%$ of respondents: feedback on work ($n = 11$, 3%); future-readiness/workplace relevance ($n = 11$, 3%); cost-effectiveness/equitable access ($n = 5$, 2%). Approximately 10% of responses were too brief or non-specific to code (e.g., "everything", "it's good").

Table 3. Content analysis of the perceived disadvantages of using artificial intelligence in medical studies ($n = 313$).

Theme	n (%)	Representative Responses
Reduced critical thinking/reasoning	135 (43%)	"it stops you from critically thinking" "Less thought goes into questions as can quickly find answers" "Detrimental to my thinking skills and problem-solving abilities as I am constantly relying on AI to breakdown paragraphs"
Over-reliance/dependence	80 (26%)	"People can become overly reliant on it to answer everything" "We don't know how dependent we are on AI for knowledge until it's not allowed anymore" "people may use it as a crutch. . . instead of just allowing it as a guiding tool"
Inaccuracy/misinformation/hallucination	75 (24%)	"AI can confidently give incorrect or outdated information" "ChatGPT has been known to make up sources" "especially dangerous. . . where your general knowledge may not be high enough to realise the information. . . doesn't sound right"
Academic integrity/cheating/plagiarism	52 (17%)	"Loss of academic integrity when it is used to write entire assignments" "unfairness for students who did the work themselves" "Increased risk of plagiarism"
Laziness/reduced effort/passive learning	36 (12%)	"seeking the short cut to answers instead of working things out your selves" "an 'easy' way out—may allow students to be passive learners rather than active" "a rapid, instant gratification for work"
Source credibility/referencing/context specificity	32 (10%)	"may not be specific to the Australian healthcare system" "uses data available on the internet—this includes like reddit or social media posts" "Paraphrasing or using information without correct referencing"
Loss of research/info-finding/academic-writing skills	31 (10%)	"strips medical students of key skills like researching, referencing, academic writing" "Reduced experience in using clinical resources required for future work as a doctor eg. eTg, AMH" "loss of ability to communicate through written form if using to write assignments"
Loss of independent thinking/creativity	18 (6%)	"loss of your own original thoughts" "limits self creativity" "Loss of ability to generate own ideas"
Reduced/shallow learning and retention	17 (5%)	"it doesn't make you think and learn, it gives you answers" "probably not as good for my long-term retention" "bypasses some learning"

Themes mentioned by $\geq 5\%$ of respondents, ranked by frequency. Responses could be coded to more than one theme, so percentages sum to more than 100%. Two to three representative responses are shown per theme to illustrate its range. Other concerns each mentioned by $<5\%$ of respondents: reduced human/interpersonal/clinical skills, e.g., empathy and communication ($n = 15$, 5%); ethical, privacy and confidentiality concerns ($n = 12$, 4%); regulatory uncertainty/institutional disapproval ($n = 7$, 2%); environmental impact ($n = 5$, 2%).

All numerical data were analysed using IBM SPSS Statistics, Version 27 (IBM Corp., Armonk, NY, USA). For the qualitative component, all free-text responses to both open-ended items (Q23, 320 respondents; Q24, 313 respondents) were read in full by the authors (T.W., N.H., E.J.), who inductively derived a coding framework following the phases outlined by Braun and Clarke [39]; each response was then coded against the framework. As most responses referred to more than one idea, responses could be assigned to multiple themes; theme frequencies are reported as the number and percentage of respondents mentioning each theme and sum to more than 100%. Themes endorsed by at least 5% of respondents are reported in Tables 2 and 3, with less frequent themes summarised in the table notes.

4.5. Ethical Considerations

The study was conducted in accordance with the Declaration of Helsinki and approved by the James Cook University Human Research Ethics Committee (approval number H6921). Participation was voluntary and anonymous. Informed consent was obtained electronically: the online questionnaire opened with an informed consent form containing the participant information, and students were required to tick a consent box ("I consent to complete the questionnaire") before proceeding to the survey items. The participant information materials stated that no identifying personal information would be collected, that responses would be analysed by the research team, and that data would be reported only in aggregate.

5. Results

5.1. Univariate Analysis

Overall, 438 of 1192 enrolled Year 1–6 medical students completed the survey (response rate 37%). Gender was reported as female by 288 respondents (66%) and male by 146 (34%); one respondent preferred not to answer, and three did not answer the item, and these four respondents were excluded from gender comparisons. The mean and median ages were 21.9 and 21 years, respectively. The sample was spread fairly evenly between pre-clinical Years 1–3 ($n = 241$; 55%) and clinical Years 4–6 ($n = 197$; 45%); by year, respondents comprised Year 1 ($n = 76$), Year 2 ($n = 94$), Year 3 ($n = 71$), Year 4 ($n = 103$), Year 5 ($n = 36$) and Year 6 ($n = 58$). Respondents were located at the Townsville ($n = 245$; 56%), Cairns ($n = 183$; 42%) and Mackay ($n = 10$; 2%) campuses.

Overall, 80% of students reported using AI for their medical studies or assignments, and a majority have been utilising AI for at least 6 months (63%), and even in everyday lives outside of medicine (72%), using a free version of AI (88%) instead of purchasing (12%). A majority of students agreed on allowing the use of AI in medical school for both study AND assignments (58%), 36% thought AI should only be used for study, and 1% thought AI should only be used for assignments, whilst very few believed medical schools should not allow students to use AI (5%).

The most common uses of AI (reported as often/always) were to explain concepts (56%); answer medical content questions (54%); answer questions you would otherwise need to ask lecturers or doctors (46%); summarise notes or lectures (37%); and help with PEAL assignments * (36%). On average, students reported that AI assisted with 30% of their assignments and 42% of their study and examination preparation, respectively. Students reported that, if AI was not utilised, the quality of their assignments and studies would be affected by 23% and 34%, respectively. Students also reported that the efficiency of their study would be affected by 46% without using AI and that the grades would be affected by 24%. In contrast to the widespread use and the impact of AI, students reported moderate

trust in AI, acknowledging that AI could be detrimental to the core values of medicine and professionalism (41%) and reduce human critical thinking ability (60%).

* Professionalism Education and Leadership (PEAL): A portion of summative assessment at JCU that questions “students on their professional and ethical reflective development and to review the evidence of progress”.

5.2. Bivariate Analysis

Differences in AI use and attitudes by year level and gender are presented in Table 1. The year-level differences that remained significant after correction were: using AI to ask medical content questions, to explain concepts, and to ask questions otherwise directed to lecturers or doctors (all higher among pre-clinical students) and use for patient case reports and case logs (higher among clinical students). Gender differences remaining significant after correction were: paying for AI, duration of use, use for objective structured clinical examination and multi station assessment task practice, professionalism assignments, scientific writing, patient case reports and case logs, and support for allowing AI for both study and assignments (all higher among male students). Differences in the 0–100 scale items (e.g., greater reported study-related reliance among pre-clinical students and greater trust among male students) are shown in Table 1.

5.3. Content Analysis

Written comments in the open-ended questions reported that Google now has a built-in AI summary, meaning that many students no longer need to create an account with a website to access an AI model, resulting in only 9% of students paying for access to a fee-for-service AI program. The prevalence of capable free applications (for example, AI summaries integrated into search engines, Gemini and ChatGPT) likely removes the need for most students to purchase a paid program.

Perceived advantages (Q23, Table 2). The most frequently cited benefit by a wide margin was improved efficiency and time savings, noted by more than half of respondents (52%). Many also valued AI for explaining or simplifying difficult concepts (32%) and for summarising notes, lectures and literature (19%). Assessment-oriented uses were prominent, including generating practice questions for self-testing (16%) and creating OSCE or case-based scenarios for clinical-skills practice (8%). Students further described AI as support for academic work, including assistance with structuring, editing and grammar (15%); idea generation and brainstorming (8%); and automating tedious or low-value tasks such as case logs (7%). Additional themes included quick access to information (11%), availability when teaching staff were not (6%) and personalised or adaptive explanations (5%).

Perceived disadvantages (Q24, Table 3). Reduced critical thinking and reasoning was overwhelmingly the most common concern, raised by 43% of respondents. Over-reliance or dependence on AI (26%) and concerns about inaccuracy, misinformation and “hallucinated” content (24%) followed. Threats to academic integrity through cheating, plagiarism and submitting AI-written assignments were noted by 17%. Further concerns included AI fostering laziness and passive learning (12%); questionable source credibility and limited local (Australian/JCU) applicability (10%); and erosion of research, information-finding and academic-writing skills (10%). Smaller groups highlighted loss of independent thinking and creativity (6%) and shallow learning with poorer retention (5%).

6. Discussion

6.1. Principal Findings

This single-institution study explored artificial intelligence (AI) use among medical students across all year levels at JCU in Northern Queensland, Australia. To our knowledge,

it is the first regional Australian study to examine AI use in this population. Our findings show that AI has become a mainstream educational tool. Around 80% of students reported using it regularly for study and assessment, and 95% supported its inclusion in medical education in some capacity. Students most often turned to AI for clarifying concepts, answering medical questions, summarising content and preparing for examinations. This pattern highlights its role as a key learning aid.

Students also reported a substantial sense of reliance on the technology. They anticipated that, without AI, their study efficiency, quality of learning and academic performance would all decline. These are subjective appraisals rather than measured effects. Even so, they suggest that widespread adoption is driven by AI's perceived value for academic productivity and learning. Acceptance, however, was not unqualified. Students raised clear concerns about academic integrity, the accuracy of AI-generated information and possible effects on critical thinking.

Although conducted at a single regional institution, these patterns are unlikely to be purely local. The behaviours students described, using AI mainly for efficiency, simplification, summarising and self-testing while fearing the erosion of their own critical thinking, mirror findings from medical schools internationally [37]. We therefore read our results not as a parochial evaluation but as a theory-informed case of a transition occurring across health professions education globally and draw out transferable implications throughout this discussion.

6.2. Differences Between Pre-Clinical and Clinical Students

Differences observed between pre-clinical and clinical year students provide further insight into patterns of AI use. As previously mentioned in methods (study design and participants), the 6-year MBBS degree at JCU is split into 3 years of pre-clinical basic sciences (Years 1–3) and 3 years of clinical medicine (Years 4–6). Students in the pre-clinical years were more likely to use AI for study-related tasks, such as summarising notes and lectures and clarifying concepts and questions. In contrast, clinical year students were more likely to use AI for assessment-related tasks, including OSCE/MSAT examination preparation and assignments such as case reports and case logs. Overall, pre-clinical students reported higher use of AI for study and examination preparation than clinical year students; after correction for multiple comparisons, the differences that remained significant related to using AI to explain concepts, answer medical content questions and answer questions otherwise directed to teaching staff, while clinical students' greater use for patient case reports and case logs also remained significant. They were also more likely to perceive that the quality of their learning and examination performance would be adversely affected in the absence of AI tools.

Furthermore, as generative AI platforms became publicly accessible from 2022, students currently in the pre-clinical years could have had exposure to AI prior to enrolling into medicine or early in their medical training [40] and thus more likely to have greater familiarity to integrate AI into foundational learning processes. Findings were similarly shown in a comparative study by Maurat and colleagues wherein first-year University students exhibited highest usage of AI given their early exposure to AI during their academic career [30]. In contrast, clinical students had developed their foundational knowledge and study habits without the use of AI and more selectively utilised AI as a supplementary tool rather than an essential component of study. Additionally, as students progress through the JCU MBBS program, learning shifts from examination-focused, content-based study to assignment-driven, clinically oriented training, which may have contributed to this disparity. This interpretation aligns with established technology adoption models,

which emphasise the role of prior experience and habit formation in shaping patterns of use [28,29].

6.3. Gender Differences in Perception and Utilisation

Differences were also observed between genders. Male students were more likely to pay for AI services, use AI to clarify questions, assist in examination preparation and most particularly in assignments (OSCE/MSAT practice, medical professionalism, scientific writing, patient case reports and case logs), as well as higher levels of trust in AI outputs. In contrast, female students consistently demonstrated the importance of reliability, privacy, and ethical implications, concerns on academic dishonesty, AI inaccuracies, and potential regression of problem-solving skills. A systematic review comparing gender different usage of AI in higher education showed similar findings [31], with male students overall reporting higher usage frequency, familiarity, usability, and inclined adoption with strong perceptions of efficiency and usefulness in AI compared to female students.

These responses mirror findings from cross-sectional studies of gender differences in the general population. Across varied age groups, females have shown lower AI use, less positive attitudes towards the technology, greater concern about its economic and social implications, and higher levels of 'AI anxiety' [32–34]. One explanation offered in the literature relates to risk perception. Gender differences in how risk is perceived may shape both trust in AI and willingness to adopt it. A meta-analysis of 150 studies, for instance, found greater risk propensity among males [35]. Our study, however, did not measure risk perception, attitude formation or any underlying mechanism. These explanations therefore remain speculative in relation to our data and should be tested directly in future research.

6.4. Perceived Benefits

A key benefit of AI is its accessibility. These tools are low cost, widely available and can be used at any time. Students can get academic support immediately, without waiting for scheduled teaching or staff availability. This matters in medicine. Students must absorb a high volume of complex information, and much of the synthesising and clarifying happens outside formal teaching hours. Constant access may also promote independent learning. Students can explore topics at their own pace, free from the perceived judgment of peers or faculty. This is especially relevant in large-group settings, where many students are reluctant to ask questions openly.

Another major advantage is personalised learning. AI tools can tailor explanations to a learner's level of understanding, adjust the depth and style of their responses, and clarify further through follow-up questions. This offers a more individualised experience than traditional one-size-fits-all teaching, and it can support students with differing academic needs. Consistent with this, many students in our study reported generating their own practice questions, case scenarios and explanations.

These perceptions were reflected in students' free-text responses (Table 2): timesaving and efficiency was the most frequently cited benefit (52%), followed by explaining or simplifying difficult concepts (32%), summarising notes and literature (19%), and generating practice questions for self-testing (16%), patterns that echo cross-sectional findings elsewhere [37].

Lastly, AI enables students to cognitively offload complex concepts into a technology that retains this information. This may allow students to focus on more important cognitive operations, such as information synthesis, generating practice questions, etc.

6.5. Potential Risks of Overreliance

The risks discussed in this subsection are potential risks identified in the published literature and in students' own perceptions; they were not directly measured in this study,

and our data cannot demonstrate effects of AI use on cognition, learning, competence or patient safety.

Students' free-text responses (Table 3) reinforced these concerns. Reduced critical thinking was the most frequently raised disadvantage (43%), ahead of over-reliance (26%), inaccurate or fabricated information (24%) and threats to academic integrity (17%); the last is an increasingly recognised tension as AI becomes embedded in assessment, prompting calls for explicit guidance on acceptable use and for assessment redesign that rewards demonstrable reasoning rather than polished output [27].

Students also perceived limitations and risks with AI-supported study habits. The foremost risk identified across cohorts was the risk to critical thinking and problem-solving ability. Prior to AI's adoption, students studied actively through independent synthesis of information from textbooks and lectures. Now, AI allows 'cognitive offloading' [17], such that the burden of synthesis of information no longer falls on the student but is rather passed off onto AI. Cognitive Load Theory suggests in spite of cognitive load reduction, over-reliance on AI could significantly reduce learning promotion and cognitive absorption needed to acquire long-term memory [18]. A potential consequence could be that students become less well-versed in foundational understanding and critical thinking than what would have occurred prior to AI's adoption. Now, with AI, students rely more on external references rather than their own information formulated and memorised through personal, active, and engaged learning. Whilst AI lures students with instant gratification of cognitive load relief and productivity enhancement, studies suggest that over-reliance can diminish critical thinking, memory consolidation, and long-term knowledge retention [19,20]. Therefore, although AI can provide accessible, simplified information whilst minimising insignificant information or administrative burden, it could at the same time eliminate opportunities and learning effort for students to build competence with tasks such as generating original ideas, repeated learning for consolidating long-term memories, working through uncertainty, creating personalised study habits and recognising one's own errors.

This emerging study habit may have significant implications for future clinicians, who require continuous critical thinking and clinical reasoning skills developed through repeated exposure to uncertainty, error and iterative problem-solving that can then be applied and adapted across diverse clinical situations. Over-reliance on AI-generated answers bypasses these essential learning mechanisms and may foster illusory competence, in which students perceive a false sense of fluency without the cognitive scaffolding required for independent reasoning and genuine comprehension [21].

AI use may reduce the cognitive effort of study, and this could have consequences for resilience. Medical graduates face heavy workloads and more than a decade of training beyond their degree [41]. These demands are often seen in a negative light. Yet they can also act as developmental experiences, shaping clinicians who are resilient, competent and compassionate. Over-reliance on AI may narrow students' exposure to the cognitive, workload and emotional challenges that build this capacity. Universities therefore need to define the role of AI in medical education. Graduates must still get enough practice managing sustained and demanding cognitive workloads because these will follow them across their careers.

Moreover, the uncertainty about the accuracy of AI outputs further complicates these risks. ChatGPT, one of the most widely used AI chatbots, states that the tool "can produce incorrect or misleading outputs" [22]. A randomised trial involving medical students found that incorrect AI-generated medical information significantly reduced diagnostic accuracy and impaired students' ability to make independent decisions confidently; concerning, some students accepted inaccurate AI-generated suggestions even when the

information was misleading or incorrect [23]. A similar though smaller effect has been shown in clinicians whose diagnostic accuracy fell when they were given incorrect AI information [24]. AI has also been shown to provide inconsistent responses to healthcare-related decisions, leading the authors of one study argue that AI is currently an inadequate learning tool for healthcare learners and professionals [25]. Together, these studies suggest that over-reliance on AI can pose a substantial safety risk in healthcare and that AI is inappropriate as a sole agent of learning for students and professionals, given that students and doctors appear concerningly reluctant to reject incorrect outputs because of their trust in AI.

To overcome these limitations, AI-supported study should promote effortful engagement rather than passive reception of information, and students and clinicians should receive training and support to critically assess AI recommendations when making clinical decisions without AI-reliance [26]. Importantly, the implications extend beyond academic performance into professional identity formation. Almost half of students in this study believed AI can be detrimental to the core values of medicine and professionalism. Medicine is a human-centred profession requiring communication skills, empathy, ethical reasoning and professionalism. These competencies are cultivated progressively through patient interaction, collaborative discussion, and exposure to nuanced clinical dilemmas during training involving real-life clinical interaction. Such situations are often ambiguous creating varied experience and outcome with patient preferences, considerations, circumstances, and ethical principles that cannot be fully addressed through algorithmic outputs alone. Over-reliance on AI may reduce opportunities for students to independently interpret patient narratives, formulate nuanced clinical judgements, or critically reflect on ethical dimensions of care. Over time, this may result in clinicians with insufficient humanistic competencies who may lack safe and compassionate patient care.

6.6. Socio-Technical and Ethical Considerations and Open Research Questions

Several socio-technical properties of large language models affect their educational use. These systems are typically trained on broad, general-purpose corpora rather than carefully curated medical datasets. As a result, they can generate realistic but entirely false information, often referred to as 'hallucinations' [22,25]. Students in our study were aware of this risk. They recognised the potential inaccuracy of AI-generated content and were concerned about its source credibility (Table 3). Adoption of generative AI is also shaped by social factors. Students take up these tools largely through peer influence, particularly in collaborative study environments and through online recommendation, or 'electronic word-of-mouth' [28,29,36]. The integration of AI into assessment therefore raises unresolved ethical concerns. These include maintaining assessment integrity, ensuring transparency, and providing fair access when powerful commercial tools sit behind paywalls [27].

Learning behaviours in collaborative academic environments are also shaped by peer norms. Students tend to adopt the study approaches that are widely used and accepted within their social and educational networks. The Technology Acceptance Model (TAM) helps explain this pattern. TAM proposes that adoption depends on two key factors: perceived usefulness and perceived ease of use [36]. The more useful and easy to use a technology appears, the more likely people are to take it up. Generative AI platforms fit this model well. They are simple in design and require little instruction to use. A short text prompt returns tailored information within seconds. This shifts the traditional mindset of working through a problem to reach a solution. Our findings reflect both TAM factors clearly. Students estimated that without AI, their study efficiency would drop by 46% and their grades by 24% on average. These figures point to how central perceived usefulness

has become. AI adoption among medical students is therefore not simply opportunistic. It reflects a clear recognition of the technology's functional benefits and its accessibility.

This study opens several questions for future research. How does generative AI use change over time and across settings? What is its long-term impact on clinical reasoning, independent problem-solving and assessment design? Future work should also develop AI literacy interventions and test whether the verification behaviours they teach transfer to clinical decision-making. Longitudinal studies are needed to examine how peer influence and electronic word-of-mouth shape students' choice of clinical AI tools and how unequal access to paid AI tools interacts with efforts to build clinical AI education.

6.7. Strengths and Limitations

This study has several notable strengths, foremost among them being one of the largest Australian studies examining AI uptake among medical students over six years of pre-clinical and clinical medicine. Importantly, this study was also conducted within a regional medical school setting in Australia, addressing a gap in the current literature, which has largely focused on metropolitan or internationally based institutions. The broad demographic diversity captured in this study enhances the significance and applicability of the findings to broader medical student populations nationally and internationally. The design, including both quantitative and qualitative content analysis, improves the thoroughness of analysis by capturing usage patterns and student perceptions, attitudes, and concerns about its educational and clinical impact.

This study has a few limitations. It was conducted at a single Australian institution, and although the response rate (37%) is consistent with comparable online student surveys, non-response and self-selection may have skewed participation toward students with stronger views about AI. The data are self-reported and cross-sectional, capturing perceptions and estimated behaviours at a single point in time during fast technological change rather than verified usage or causal relationships; estimates such as the perceived fall in study efficiency without AI should be read as subjective appraisals. The social desirability bias may have led students to underreport uses they perceived as academically questionable. The convergence of our themes with those reported in other settings suggests these limitations do not undermine the broader transferability of the findings. Year 1 students were surveyed later in the academic year than other cohorts. At the same time, this was necessary for them to have developed stable study habits, their responses reflect a different exposure period, and year-level comparisons involving Year 1 should be interpreted with this in mind. The study had no metropolitan comparison group, so it cannot establish whether regional location itself influences AI uptake. Finally, gender comparisons were exploratory; the mechanisms underlying observed differences were not measured. Subsequent studies should track AI use longitudinally and incorporate objective measures of actual use and educational impact, as self-reported data cannot fully capture how rapidly evolving AI tools are being used or their effects on cognition and performance. Given the speed of technological change, ongoing monitoring of student AI use and of its effects among different student groups will be needed to ensure that findings remain current.

7. Conclusions

Generative AI is now part of everyday study for students at this regional Australian medical school. Most students use it to learn and prepare for assessment. They value it for speed and for helping them understand difficult content. Students' concerns centre on critical thinking, academic integrity and the reliability of AI-generated information. Because this was a cross-sectional, self-report study, these findings describe patterns of

use and perception; they do not demonstrate effects of AI on learning, grades, cognition, competence, professionalism or patient safety.

Within these limits, the implications are practical and specific. Rather than prohibiting a technology students have already embedded in their study, medical schools should: adopt explicit, assessment-aligned policies defining acceptable AI use for each assessment type; embed AI literacy training that teaches students to question, verify and appropriately bound AI outputs; develop ethical use guidelines addressing integrity, transparency and disclosure; and redesign assessment to reward demonstrable independent reasoning, academic writing and evidence appraisal—the skills students themselves perceive to be most at risk. Future longitudinal research incorporating objective usage and cognitive measures is needed to determine the actual educational impact of generative AI in medicine.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/ime5030089/s1>, Supplementary Material File S1: Survey Instrument: Utilisation of Artificial Intelligence (AI)/Generative AI for Learning and Assessment amongst Medical Students.

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