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The use and usefulness of GenAI in higher education: Student experience and perspectives

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ABSTRACT

Higher education institutions face the need to support learners' access to and use of generative artificial intelligence (GenAI) in appropriate and effective ways. However, the rapid growth of GenAI means that policy and practice has evolved with limited empirical data about student experience, attitudes, and motivations. In response, this paper reports on a large-scale multi-institution survey of over 8000 students studying at four Australian universities. We examine the frequency and purpose of GenAI usage, identifying key demographic variations in engagement. Our findings show that over 80% of students have used GenAI for study-related tasks, with nearly half using it regularly, primarily for editing, summarising, and idea generation. Usefulness, rather than blind trust or rule compliance, appears to drive this engagement. Students adopt GenAI pragmatically, with low trust in its factual accuracy, but confidence in their own ability to manage it as a support tool for academic work. We also investigate how students learn about these tools, finding that most rely on informal, self-directed learning rather than institutional resources, raising questions about the adequacy of current university guidance. Equity gaps in access and usage are evident, with proportionately lower engagement with GenAI tools among women, non-binary, neurodivergent students, and those with health conditions. While most students avoid prohibited use, a significant minority report behaviour that contravenes policy, pointing to a need for more nuanced and situationally aware approaches to academic integrity. These findings offer critical insights for institutional responses.

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1. Introduction

Generative artificial intelligence (GenAI) became readily accessible to all staff and students in higher education with the public release of the Large Language Model (LLM) powered tool OpenAI ChatGPT in November 2022. Numerous competing models soon followed, some enhanced by Large Multimodal Models (LMMs), capable of processing speech and images in addition to texts. 2023 marked the rapid integration of GenAI resulting in "extremist attitudes ranging from enthusiasm to undue fear" ([1], p.2). The immediate preoccupation for many higher education institutions was fear that students were using these tools to cheat in assessment tasks [2], and institutions faced a quandary as to how this threat could be managed [3]. Despite the severity of the assumptions made about such student uses of GenAI, little evidence has been collected to understand the nuances of student use, values, and beliefs about using GenAI for study, assessment, and research [4]. Where such evidence has been collected, it has mostly been limited to small scale preliminary studies [5–7]. Without an evidence-based foundation, it is easy to fall back on assumptions or simplistic views of human-technology interactions to make sense of the situation, resulting in reactionary policy, inadequate practice responses, and poor student interactions with GenAI [8].

Higher education institutions are responding to GenAI in the absence of robust, large-scale evidence about how students actually use these tools, how they learn about them, and what shapes their decisions [5]. Existing assumptions risk oversimplifying student behaviour and leading to reactionary or misaligned policy and practice. Therefore, the objective of this study is to better understand how university students engage with GenAI in their studies, including patterns of use, sources of learning, perceptions of competence and trust, academic applications and usefulness, academic integrity behaviours, and the factors that motivate or discourage adoption. By examining these dimensions from a large-scale, cross-sectional survey conducted across four Australian universities ($N = 8021$), this study aims to contribute an evidence base capable of informing more nuanced and effective institutional responses.

2. Literature review

Early research following the release of ChatGPT reveals a rapidly shifting landscape of student awareness and usage across contexts and time. A. Kelly et al. [6] found 41 % of 1135 Australian university students surveyed in March 2023 had minimal or no awareness of GenAI tools, and of those who had heard of GenAI, few had ever used it. In a larger UK study of 2555 students in early 2023, Johnston et al. [9] identified higher awareness of ChatGPT (68.9 %) among University of Liverpool students, examining personal, academic and professional usage, but not frequency. In November 2023, He et al. [10] studied 674 students across two campuses of Hong Kong University, and found that nearly two-thirds of the participants used the university's ChatGPT platform more than three times weekly.

Of the 6311 higher education students in Germany surveyed by von Garrel and Mayer [11] in early 2023, two-thirds stated they had used AI tools for study, with 25.3 % using these tools very often or frequently, 9.5 % occasionally, 12.5 % rarely or very rarely, and 36.8 % not at all. An international investigation by Ravšelj et al. [12], surveying 23,218 students across 109 countries from October 2023 to February 2024, offers greater but uneven geographical scope. The study found that 71 % of student respondents had used ChatGPT for study; but did not include information about how students became aware of GenAI tools. Further, frequency of use was linked to separate types of tasks.

A theme across the studies that we reviewed is that students predominantly discover and learn about GenAI through informal, non-institutional channels. A. Kelly et al. [6] found students primarily learned about GenAI through informal channels—social media (64 %), traditional media (41 %), peer networks (32 %), and work (20 %) rather than through their institutions. Similarly, Pallivathukal et al. [13] found healthcare students mainly discovered ChatGPT through internet sources (48.8 %) and social connections (36.7 %), with formal educational channels contributing marginally (8.8 %). These results demonstrate that students are using their everyday information channels to learn about GenAI, and may also indicate lack of communication of institutional guidance as universities worked to establish their particular positions on appropriate GenAI use.

Research into student competence and trust in GenAI reveals nuanced and sometimes contradictory dynamics that influence tool usage. A. Kelly et al. [6] reported the counterintuitive finding that 15 % of students who had never used GenAI tools nonetheless expressed confidence in their ability to use them. Amoozadeh et al. [14] identified considerable variation in trust levels among computer science students (16 % distrust, 36 % neutral, 47 % trust) and found correlations between trust and motivation. In a longitudinal study, Polyportis [8] positioned trust as a key psychological factor influencing human-AI relationships but observed decreasing ChatGPT usage over time, contrary to typical technology adoption patterns. These findings suggest nuanced relationships between trust, perceived competence, and usage behaviours that bear further examination.

Existing studies have begun to map the academic applications of GenAI and explore its perceived usefulness in supporting student tasks. Chan and Hu [15] identified qualitative themes around information retrieval, brainstorming, content summarization, creating visuals, and managing repetitive administrative tasks. Johnston et al. [9] focused on academic writing purposes, with grammar checking and reference assistance emerging as common academic applications. Liu et al. [16] examined academic language-related applications specifically, finding more positive perceptions for writing and reading than for speaking skills. Ravšelj et al.'s [12] study identified brainstorming (29 %), summarization (27 %), research assistance (25 %), and academic writing (22 %) as primary applications.

Concerns around academic integrity remain central in GenAI discourse, with studies exploring how students differentiate between ethical and unethical usage, and how institutions can respond [17,18]. GenAI seems to be blurring the prevailing boundaries of academic misconduct. Students interviewed by Verma [19], for instance, shared three distinctions between unethical and ethical use of GenAI tools, perceiving 1) GenAI authorship being equivalent to plagiarism, 2) GenAI acting as a helpful tutor but requiring critical appraisal before using in assessment tasks, and 3) GenAI as a source of ideas and concepts but not final work. Johnston et al. [9] found that over 70 % of students were not supportive of other students using GenAI tools to complete whole assessment responses and that the university needs a policy on appropriate use of these technologies. Similarly, Yusuf's et al. [7] multicultural survey with 708 students across 76 different countries found that 54.5 % had not used GenAI for plagiarism and would not do so in the future, a further 6 % had not used it for this reason but would do so in the future, 19.2 % had used it previously for plagiarising but would not do so in the future, and 19.9 % had used it and would continue to do so. These authors agree on the need for policies that can balance the benefits of using GenAI with considerations for academic integrity and student learning.

Despite growing interest in GenAI, the motivational and contextual factors shaping student adoption remain poorly understood. Tiwari et al. [20] noted that while students enjoyed using these tools and found them useful, students did not find ChatGPT easy to use, particularly for efficiency-oriented students. In a study at Utrecht University [21], students were concerned about becoming over-reliant on GenAI for coding, while using GenAI for summarizing readings and troubleshooting code was noted by Sallai et al. [22] as a stress response to deadlines rather than a desire to learn more deeply. Chan and Hu [15] identified concerns including accuracy, transparency, privacy, ethical considerations, and impacts on critical thinking, but did not quantify their relative importance or interaction with motivating factors. Johnston et al. [9] briefly mentioned access inequality to premium versions as a constraint but without systematic examination. More research is needed to appreciate the implications of these significant and evolving issues.

Considering this literature as a whole, allows us to identify dimensions regarding how students use AI. These elements are: a) what are students are using GenAI for; b) feelings of usefulness with respect to GenAI; c) frequency of use of GenAI; d) feelings of competency with respect to using GenAI; e) how much they trust GenAI; f) how they learned to use GenAI; g) whether Gen AI is being used to cheat; h): what motivates or discourses their use of GenAI. These dimensions collectively provide a more comprehensive insight into student use across multiple dimensions. However, studies thus far have been somewhat piecemeal across these dimensions.

Despite this growing body of work outlined above, our understanding regarding student use of AI is constrained in several significant ways. First, the majority of studies rely on limited sample sizes from single institutions. Second, methodological inconsistencies make comparative analysis difficult, with studies examining different aspects of student engagement using varied measurement approaches. Finally, the rapid evolution of both the technology itself, and student familiarity and skill, means findings quickly become outdated.

These substantial gaps underscore the continued need for more comprehensive and methodologically robust research on student engagement with GenAI. The present study addresses these limitations by examining experiences of over 8000 students across four Australian universities, providing greater scale, demographic diversity, and analytic depth than previous studies.

By investigating frequency of use across demographic groups, sources of GenAI knowledge, perceived competence and trust, specific academic applications, and factors influencing adoption, this research offers a more nuanced picture of how students navigate the GenAI landscape. This, in turn, can support the development of evidence-based policies and pedagogical approaches in an increasingly AI-mediated educational environment.

3. Method

This paper reports on a large-scale, cross-sectional survey that sought to understand how students used GenAI in their studies, the perceived usefulness of GenAI, and the factors that influenced their use. We selected a cross-sectional survey study as we aimed to understand the attitudes and behaviours of GenAI use across a large population. It is a relatively quick and inexpensive study design ensuring our findings are timely and relevant, and can be used to further explore more in-depth themes as this rapid area progresses [23].

3.1. Context

Students were surveyed from four Australian universities. In late 2023, A consortium of researchers from these institutions was formed to focus on student perspectives around GenAI, which were at risk of being overlooked [3]. At the time of the survey, none of the universities were banning the use of GenAI outright, but were yet to develop institutional policies, devolving the decision to individual unit/ course levels to explain and enforce any GenAI restrictions. As a parallel focus group study suggested, irrespective of institutions, students had a shared sense of confusion around what they were and were not permitted to do, relying instead on their own moral judgements [4]. The higher education sector in Australia has been strongly guided by the national regulator, who by 2023 had provided principles to guide approaches to assessment [24].

3.2. Participants

Participation in this study was voluntary and anonymous. The sampling frame consisted of coursework students enrolled at the undergraduate or postgraduate level. Recruitment was restricted to the researchers' respective universities, resulting in a convenience sample. Each institution adhered to its own sanctioned distribution processes, which included notification via email to all students (University of Queensland, University of Technology Sydney), Learning Management System notifications (Monash University), and via notices posted by individual subject/unit coordinators (Deakin University).

Approximately 192,000 students from the four Australian universities were invited to participate in the online survey, and 5 % ($N = 10{,}132$) of students volunteered. Of those, 79 % ($N = 8021$) completed the full survey, with a further 8 % ($N = 826$) who completed at least part of the survey. Of those who completed the full survey, 583 responses were from Deakin University, 3859 responses were from Monash University, 2582 responses were from University of Queensland, and 997 responses were from University of Technology Sydney. Given the scale of response, only completed surveys are included in this analysis. However, some items report different N values which reflects the fact that some students may have chosen different items from a list, or had additional questions depending on their earlier responses (see [25] for the survey items and survey flow). Degree levels spanned undergraduate, postgraduate and doctorate. The demographic breakdown of participants can be found at Appendix A.

3.3. Survey

The survey instrument along with a description of its construction and testing is published under a Creative Commons BY-NC-SA 4.0 license [25]. The survey items were initially developed through review of existing surveys and scales from empirical studies and reports (e.g., [26, 27]; Ipsos MORI, 2017; [28–30]) on public and students' AI literacy, trust in AI, attitudes towards AI and technology, AI uses, and emotional and attitudinal antecedents of AI and technology use. These studies informed the construction of thematic topics and propositional items for the main survey sections of knowledge and access, use and usefulness, and attitudes about GenAI. After that, the survey themes and items were further developed and enriched through multiple rounds of consultations with 19 experts in higher education (expertise including AI in education, educational technology, digital and online learning, curriculum and learning design, assessment and academic integrity, student experience and wellbeing). In addition, the survey underwent a process of piloting and refinement to strengthen content validity and usability. During the process, we invited 5 academic staff and 21 students (including 14 undergraduate and 7 postgraduate students, 14 domestic and 7 international students) from the participating universities to test the survey, providing feedback on question clarity, comprehension, and usability (see [25], for further details about the survey construction and piloting).

In this paper, along with demographic items, we explore a selection of questions relating to student use of GenAI for study. These fall broadly into six lines of inquiry:

- How frequently is GenAI used for study purposes? (Q34)
- How are students learning about GenAI? (Q26, Q27)
- Do they feel competent in using it (Q19), and do they trust it? (Q22)
- What are they using it for (Q35, Q37), and how useful is it? (Q36, Q38.1)
- Are students using GenAI to cheat? (Q32)
- What motivates (Q45) and discourages (Q47) their use of GenAI?

Table 1
Frequency of GenAI use by demographic characteristics.

		How often do you use GenAI tools for university study?										
		N	I have never used it (1)		Less often (2)		Monthly (3)		Weekly (4)		Daily (5)	
			n	%	*n*	%	*n*	%	*n*	%	*n*	%
Whole sample		8458	1419	16.8 %	1969	23.3 %	1311	15.5 %	2627	31.1 %	1132	13.4 %
Age	18–19	1763	295	16.7 %	407	23.1 %	311	17.6 %	563	31.9 %	187	10.6 %
	20–24	4156	572	13.8 %	957	23.0 %	674	16.2 %	1390	33.4 %	563	13.5 %
	25–29	1229	216	17.6 %	288	23.4 %	169	13.8 %	351	28.6 %	205	16.7 %
	30–34	531	105	19.8 %	122	23.0 %	63	11.9 %	146	27.5 %	95	17.9 %
	35–39	308	74	24.0 %	72	23.4 %	41	13.3 %	79	25.6 %	42	13.6 %
	40–44	181	51	28.2 %	45	24.9 %	18	9.9 %	46	25.4 %	21	11.6 %
	45 and over	290	106	36.6 %	78	26.9 %	35	12.1 %	52	17.9 %	19	6.6 %
	Total	8458	1419		1969		1311		2627		1132	
Gender	Woman	4862	848	17.4 %	1222	25.1 %	819	16.8 %	1472	30.3 %	501	10.3 %
	Man	3209	439	13.7 %	637	19.9 %	435	13.6 %	1103	34.4 %	595	18.5 %
	Other than ‘woman’ and ‘man’	286	104	36.4 %	76	26.6 %	40	14.0 %	39	13.6 %	27	9.4 %
	Prefer not to say	101	28	27.7 %	34	33.7 %	17	16.8 %	13	12.9 %	9	8.9 %
	Total	8458	1419		1969		1311		2627		1132	
Enrolment type?	Domestic student	5303	1200	22.6 %	1316	24.8 %	871	16.4 %	1468	27.7 %	448	8.4 %
	International student	3155	219	6.9 %	653	20.7 %	440	13.9 %	1159	36.7 %	684	21.7 %
	Total	8458	1419		1969		1311		2627		1132	
Course level	Undergraduate	5164	892	17.3 %	1251	24.2 %	846	16.4 %	1596	30.9 %	579	11.2 %
	Graduate	2821	452	16.0 %	594	21.1 %	404	14.3 %	919	32.6 %	452	16.0 %
	Doctorate/PhD	473	75	15.9 %	124	26.2 %	61	12.9 %	112	23.7 %	101	21.4 %
	Total	8458	1419		1969		1311		2627		1132	
Broad discipline	STEM	2646	329	12.4 %	525	19.8 %	364	13.8 %	915	34.6 %	513	19.4 %
	HEALTH	1995	425	21.3 %	528	26.5 %	326	16.3 %	527	26.4 %	189	9.5 %
	HASS	1700	378	22.2 %	476	28.0 %	271	15.9 %	436	25.6 %	139	8.2 %
	BUSLAW	1429	155	10.8 %	272	19.0 %	240	16.8 %	534	37.4 %	228	16.0 %
	Total	7770	1287		1801		1201		2412		1069	
Years enrolled in degree	Up to 1 year	1600	326	20.4 %	374	23.4 %	230	14.4 %	491	30.7 %	179	11.2 %
	2 years	1362	206	15.1 %	336	24.7 %	232	17.0 %	435	31.9 %	153	11.2 %
	3 years	1203	178	14.8 %	288	23.9 %	220	18.3 %	375	31.2 %	142	11.8 %
	4 years	709	120	16.9 %	177	25.0 %	112	15.8 %	219	30.9 %	81	11.4 %
	5 or more years	290	62	21.4 %	76	26.2 %	52	17.9 %	76	26.2 %	24	8.3 %
	Total	5164	892		1251		846		1596		579	
Main language at home	English	5196	1133	21.8 %	1303	25.1 %	847	16.3 %	1440	27.7 %	473	9.1 %
	Language other than English	3262	286	8.8 %	666	20.4 %	464	14.2 %	1187	36.4 %	659	20.2 %
	Total	8458	1419		1969		1311		2627		1132	
Disability, health or mental health condition, or neurodivergent	Yes	1808	440	24.3 %	471	26.1 %	284	15.7 %	446	24.7 %	167	9.2 %
	No	6267	904	14.4 %	1393	22.2 %	968	15.4 %	2078	33.2 %	924	14.7 %
	Prefer not to say	383	75	19.6 %	105	27.4 %	59	15.4 %	103	26.9 %	41	10.7 %
	Total	8458	1419		1969		1311		2627		1132	

Note. Percentages are row percentages. Data represents the number of students who answered this question. *Years enrolled* was only completed by undergraduate students. *Broad disciplines* include students who a) were enrolled in single degrees, or b) who were enrolled in a double degree where their main disciplines were within a single discipline area.

Table 2
Resources used to learn about AI and helpfulness of those resources.

Resources to learn about GenAI	N	%	Helpfulness							
			N	Very unhelpful (1)	Somewhat unhelpful (2)	Neither helpful nor unhelpful (3)	Somewhat helpful (4)	Very helpful (5)	M	SD
Yourself by trial and error	5134	65.7 %	5134	61 1.2 %	165 3.2 %	381 7.4 %	2356 45.9 %	2171 42.3 %	4.25	0.82
Friends, other students, or family	4350	55.7 %	4350	37 0.9 %	189 4.3 %	612 14.1 %	2483 57.1 %	1029 23.7 %	3.98	0.79
Internet searches	4087	52.3 %	4087	39 1.0 %	161 3.9 %	405 9.9 %	2167 53.0 %	1315 32.2 %	4.12	0.81
GenAI itself	3368	43.1 %	3368	41 1.2 %	176 5.2 %	464 13.8 %	1758 52.2 %	929 27.6 %	4.00	0.86
Social media	3331	42.6 %	3331	51 1.5 %	212 6.4 %	551 16.5 %	1792 53.8 %	725 21.8 %	3.88	0.87
University workshops	978	12.5 %	978	21 2.1 %	61 6.2 %	121 12.4 %	481 49.2 %	294 30.1 %	3.99	0.93
University online resources	742	9.5 %	742	17 2.3 %	39 5.3 %	108 14.6 %	346 46.6 %	232 31.3 %	3.99	0.94

Note. Data represents the number of students and percentage of sample that used the resource to learn about GenAI. Participants then rated the helpfulness of the resource.

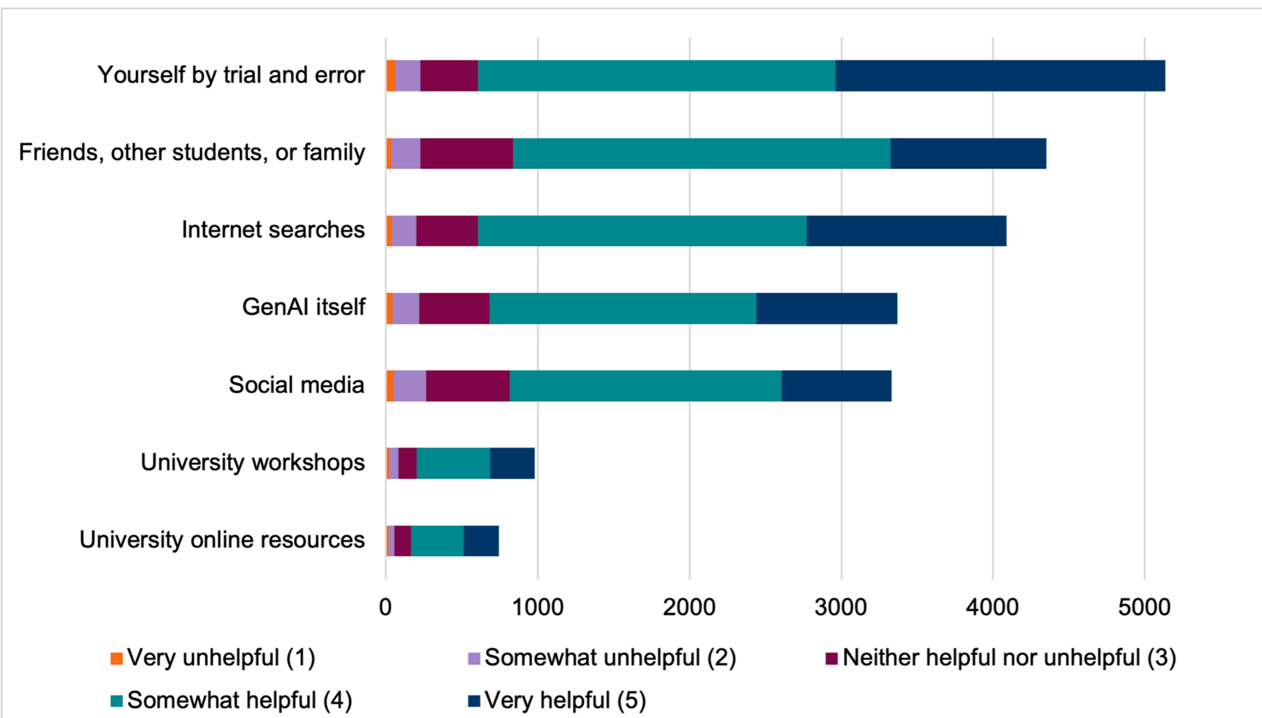

Fig. 1. Frequency of resources used to learn about GenAI and helpfulness of those resources.

Table 3
Perceptions of competence to use GenAI, and trust in its outputs.

	N	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)	*M*	*SD*
Overall, I am successful in making GenAI create outcomes that meet my needs	8847	624 7.1 %	849 9.6 %	1485 16.8 %	4387 49.6 %	1502 17.0 %	3.60	1.09
I trust what GenAI generates	8847	1674 18.9 %	2647 29.9 %	2116 23.9 %	2130 24.1 %	280 3.2 %	2.63	1.13

Note. Data represents the number of students who answered the questions.

3.4. Data collection

Approval was received from the human research ethics committees from all four universities. Recruitment of students occurred in different ways across the four universities. In two of the universities, blanket emails were sent to students, at one university an invitation was placed at the top of each course unit in the learning management system, and the final university invited unit/subject coordinators to post the

Table 4
Uses of GenAI for study and the helpfulness of those uses.

Used GenAI for	N	%	Helpfulness							
			N	Very unhelpful (1)	Somewhat unhelpful (2)	Neither helpful nor unhelpful (3)	Somewhat helpful (4)	Very helpful (5)	M	SD
Editing or improving writing	4737	67.3 %	4712	29 0.6 %	114 2.4 %	242 5.1 %	2283 48.5 %	2044 43.4 %	4.32	0.73
Generating ideas and examples	4532	64.4 %	4510	35 0.8 %	131 2.9 %	322 7.1 %	2184 48.4 %	1838 40.8 %	4.25	0.78
Summarising notes, readings or other materials	3825	54.3 %	3804	26 0.7 %	104 2.7 %	247 6.5 %	1669 43.9 %	1758 46.2 %	4.32	0.77
Teaching me how to do something	3578	50.8 %	3554	23 0.6 %	81 2.3 %	281 7.9 %	1731 48.7 %	1438 40.5 %	4.26	0.75
Getting feedback from GenAI	3461	49.7 %	3328	41 1.2 %	141 4.2 %	352 10.6 %	1981 59.5 %	813 24.4 %	4.02	0.79
Finding information or conducting research	3308	47.0 %	3292	47 1.4 %	233 7.1 %	425 12.9 %	1634 49.6 %	953 28.9 %	3.98	0.91
Generating or error-checking code, formula, mathematical calculations or data analysis	2522	35.8 %	2508	38 1.5 %	160 6.4 %	290 11.6 %	1167 46.5 %	853 34.0 %	4.05	0.92
Generating written answers or content for studies	2433	34.6 %	2418	19 0.8 %	122 5.0 %	240 9.9 %	1339 55.4 %	698 28.9 %	4.06	0.81
Transcribing lectures, class discussions or other content	1229	17.5 %	1221	7 0.6 %	33 2.7 %	114 9.3 %	521 42.7 %	546 44.7 %	4.28	0.79
Translating text or audio into another language	1133	16.1 %	1124	10 0.9 %	29 2.6 %	90 8.0 %	387 34.4 %	608 54.1 %	4.38	0.81
Generating or editing artwork, images, diagrams, graphs or slides	986	14.0 %	982	18 1.8 %	76 7.7 %	174 17.7 %	432 44.0 %	282 28.7 %	3.90	0.96
Completing part or all of an assignment	891	12.7 %	885	15 1.7 %	36 4.1 %	149 16.8 %	435 49.2 %	250 28.2 %	3.98	0.88
Generating or editing audio, music, video or other creative media	364	5.2 %	362	12 3.3 %	28 7.7 %	62 17.1 %	135 37.3 %	125 34.5 %	3.92	1.06
Other	357	5.1 %	357	13 3.6 %	14 3.9 %	41 11.5 %	109 30.5 %	180 50.4 %	4.2	1.03
Creating games, software or apps	310	4.4 %	308	4 1.3 %	20 6.5 %	51 16.6 %	120 39.0 %	113 36.7 %	4.03	0.95

Note. Data represents the number of students and percentage of sample that used GenAI for these tasks. Participants then rated how helpful the GenAI was in these tasks.

invitation to their students in their online learning management system. An incentive was offered to students for participation: the chance to win a $350 gift card voucher (one prize per university). The survey was available between August and October 2024.

3.5. Quantitative analysis

Data were cleaned, processed, and analysed using SPSS Version 29. As the main aim of this paper was to describe how university students engage with GenAI in their studies, we have predominantly chosen to use descriptives (e.g., frequencies, means, and/or standard deviations) to present the data. Appendix A explains how the creation of post hoc variables of gender and discipline were constructed. To explore whether there is a relationship between how frequently students used GenAI in their studies and factors that motivated or discouraged them, individual Spearman's Rho correlations were conducted. Correlation coefficients (r) were interpreted as very weak (0.00–.09), weak (0.10–.29), moderate (0.30–.49), strong (0.50–1.00) [31]. A total of 21 correlations were analysed between frequency of use and the various motivating and discouraging factors.

4. Results

4.1. How frequently is GenAI used for study purposes?

Overall, as shown in Table 1, 44.5 % of students use GenAI on a weekly or daily basis, while 16.8 % have never used it. However, usage patterns vary noticeably across demographic groups. For example, men use GenAI more frequently than women and are nearly twice as likely to use it daily (18.5 % vs. 10.3 %). Non-binary students and those who prefer not to disclose their gender report the lowest levels of engagement and are about twice as likely to have never used GenAI compared to men and women.

A stark contrast is also observed between domestic and international students, with international students engaging with GenAI more frequently. While only 6.9 % of international students have never used GenAI, this figure jumps to 22.6 % for domestic students. Similarly, students who speak a language other than English at home are more frequent users than native English speakers, suggesting that GenAI may have particular utility for multilingual students. Lastly, students with disabilities report lower engagement with GenAI compared to those without disabilities, highlighting a potential gap in accessibility, awareness, or relevance of AI tools within this group.

4.2. How are students learning about GenAI?

As shown in Table 2, university-provided resources (workshops and online resources) were least used by students to learn about GenAI, with use of such resources reported by approximately 1 in 10 students. The most popular approach to learning about GenAI was *yourself by trial and error* (65.7 %, $n = 5134$). The means and standard deviations associated with helpfulness suggest that respondents viewed all seven ways to learn about GenAI as similarly helpful, with a slightly higher mean value reported for *trial and error* ($M = 4.25$, $SD = 0.82$) followed by *internet searches* ($M = 4.12$, $SD = 0.81$) and *GenAI itself* ($M = 4.00$, $SD = 0.86$). In the survey instrument, we used the somewhat tautological phrase "GenAI itself" (Q26 and Q27.3) to signal to students that we recognise that the stem of the question already includes GenAI and that we are trying to capture if they had used GenAI applications (e.g., ChatGPT, Claude, Gemini) to learn about GenAI. Overall, most students report these resources as somewhat helpful. Fig. 1 provides a visual breakdown of how students rated each resource, using stacked bars to compare the

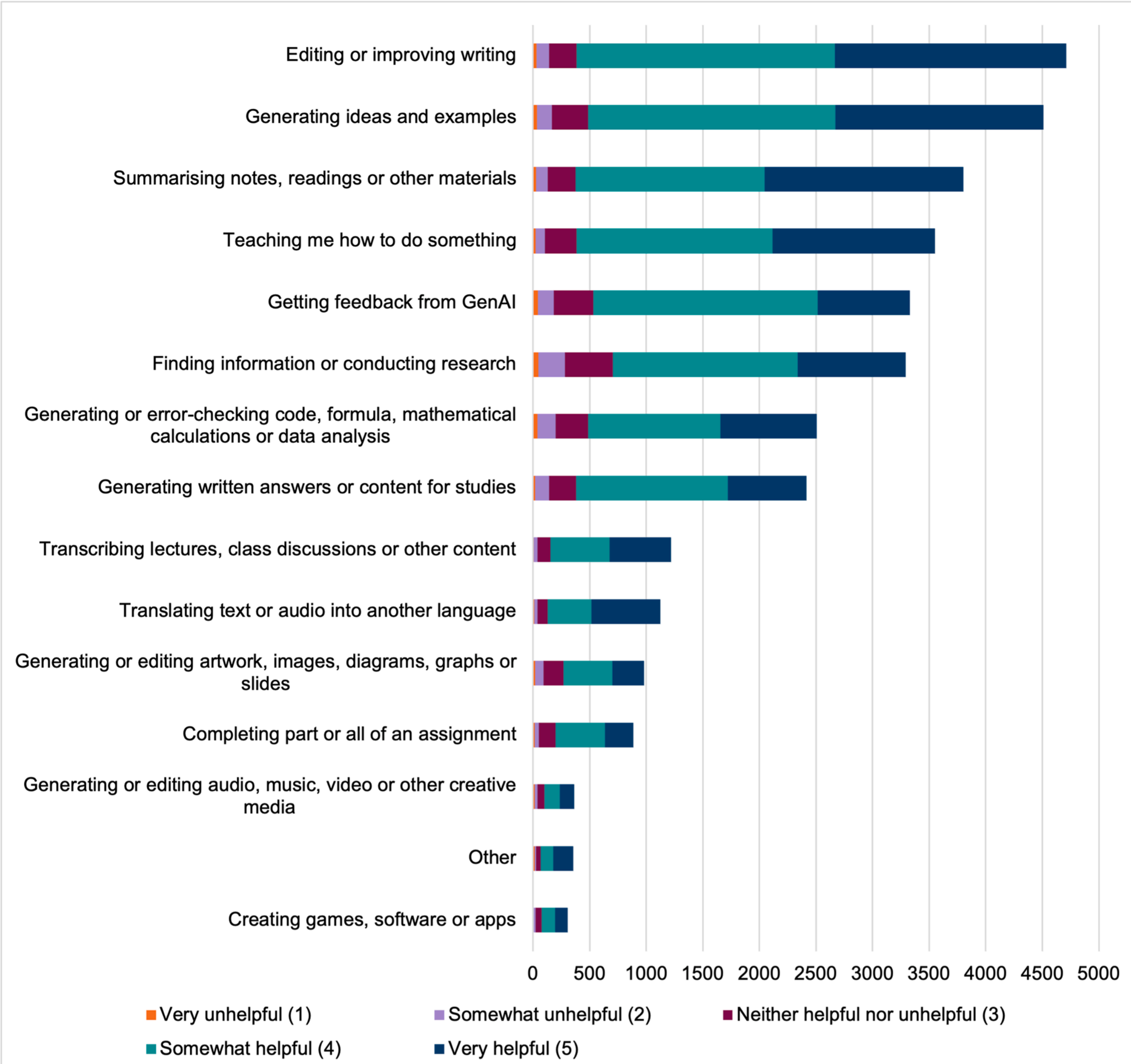

Fig. 2. Stacked bar chart of the uses of GenAI for study and the helpfulness of those uses.

Table 5
Academic Integrity.

	N	Never (1)	Sometimes (2)	About half the time (3)	Most of the time (4)	Always (5)	M	SD
Have you used GenAI to help you with assessment when you were not supposed to?	8495	5059 59.6 %	2297 27.0 %	521 6.1 %	460 5.4 %	158 1.9 %	1.63	0.95

Note. Data represents the number of students who answered this question.

relative distribution of helpfulness ratings across resources from "very unhelpful" to "very helpful."

4.3. *Are students competent in using GenAI and do they trust it?*

Table 3 presents the descriptive results of students' self-perceptions of how successful they are in getting GenAI to meet their needs, as well as how much they trust what it generates. The means and frequencies of the response choices suggest that students are more positive about their competence in using GenAI (positive 66.6 %, $n = 5889$; neutral 16.8 %, $n = 1485$; negative 16.7 %, $n = 1473$). However, they are wary of what it generates with most students either not trusting (48.8 %, $n = 4321$), or unsure (23.9 %, $n = 2116$) how much they trust, GenAI. Almost 20 % of the sample ($n = 1674$) strongly distrust what GenAI generates. Respondents who use GenAI appear more likely to trust it, however, as indicated by a significant moderate Spearman's correlation between frequency of use and trust, $r = 0.429$, $p < .001$.

Table 6
Motivating factors in the use of GenAI.

Motivating factors	N	Not at all (1)	A little (2)	A moderate amount (3)	A lot (4)	A great deal (5)	*M*	*SD*	Spearman's correlation between motivation and frequency of use: Correlation Coefficient (r)	Sig.
Makes things easier	8127	1248 15.4 %	2030 25.0 %	2009 24.7 %	1792 22.0 %	1048 12.9 %	2.92	1.26	.572**	<0.001
Makes things faster	8127	1225 15.1 %	1645 20.2 %	1706 21.0 %	2157 26.5 %	1394 17.2 %	3.10	1.32	.548**	<0.001
Improves the quality of my work	8127	1997 24.6 %	1943 23.9 %	2055 25.3 %	1394 17.2 %	738 9.1 %	2.62	1.27	.561**	<0.001
Helps me get unstuck / overcome blocks	8127	1185 14.6 %	1474 18.1 %	1872 23.0 %	2115 26.0 %	1481 18.2 %	3.15	1.32	.524**	<0.001
Helps me do things I could not do otherwise	8127	2448 30.1 %	1862 22.9 %	1799 22.1 %	1309 16.1 %	709 8.7 %	2.50	1.30	.483**	<0.001
Helps me overcome accessibility challenges	8127	4263 52.5 %	1212 14.9 %	1224 15.1 %	889 10.9 %	539 6.6 %	2.04	1.31	.269**	<0.001
Improves my English language skills	8127	3770 46.4 %	1303 16.0 %	1263 15.5 %	1129 13.9 %	662 8.1 %	2.21	1.37	.404**	<0.001
Improves my grades	8127	3097 38.1 %	1877 23.1 %	1761 21.7 %	995 12.2 %	397 4.9 %	2.23	1.22	.519**	<0.001
Reduces my stress	8127	2062 25.4 %	1768 21.8 %	1649 20.3 %	1724 21.2 %	924 11.4 %	2.71	1.35	.521**	<0.001
Is enjoyable	8127	2344 28.8 %	1831 22.5 %	1800 22.1 %	1362 16.8 %	790 9.7 %	2.56	1.32	.496**	<0.001
Helps me feel more confident	8127	2444 30.1 %	1676 20.6 %	1700 20.9 %	1490 18.3 %	817 10.1 %	2.58	1.35	.522**	<0.001

Note. ** Correlation is significant at the 0.01 level (2-tailed). The value of correlation coefficient within 0.1 - 0.29 indicates a weak relationship, within 0.3 - 0.49 indicates a moderate relationship, within 0.5 - 1 indicates a strong relationship. Data represents the number of students who answered this question.

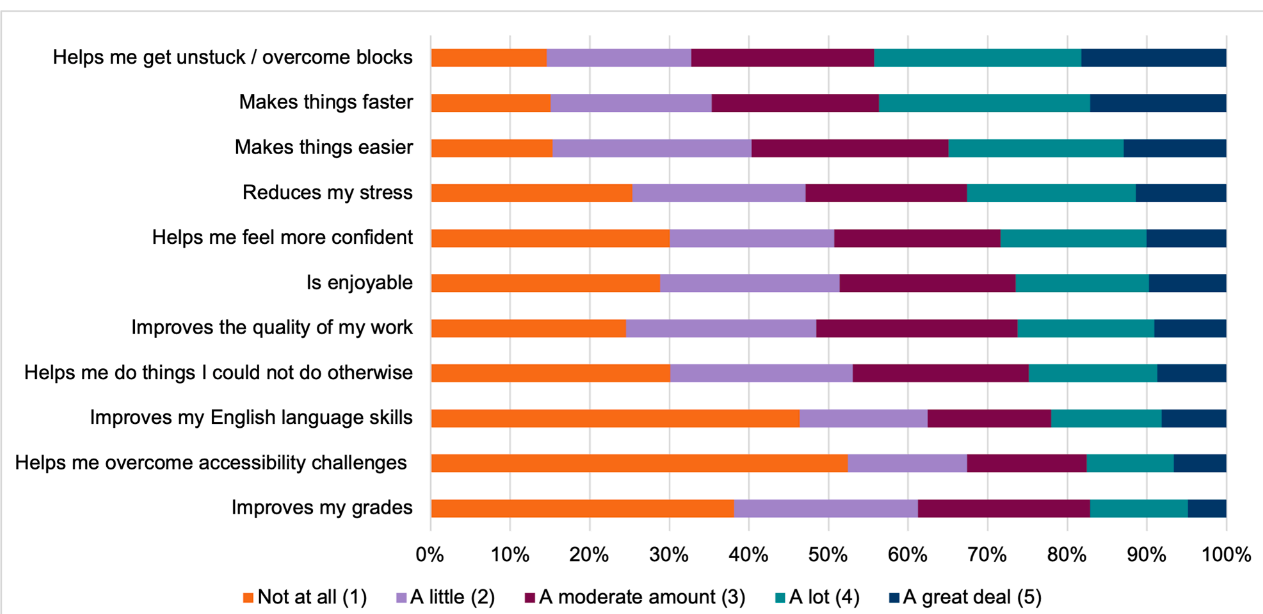

Fig. 3. Stacked bar chart of motivating factors in the use of GenAI.

4.4. What tasks do students use GenAI for, and how useful do they find it?

Students were asked to select from 15 options (including an ‘other’ category) to identify those tasks for which they use GenAI. They were subsequently asked to evaluate how helpful GenAI is in completing tasks for their studies. Table 4 indicates that the tasks most frequently identified included *editing or improving writing* (67.3 %, $n = 4737$), *generating ideas and examples* (64.4 %, $n = 4532$), *summarising notes, readings or other materials* (54.3 %, $n = 3825$), *teaching me how to do something* (50.8 %, $n = 3578$), and *getting feedback from GenAI* (49.7 %, $n = 3461$). The majority of the sample reported utilising GenAI to complete these tasks. Least used tasks, selected by fewer than 1 in 5 students, included *transcribing lectures, class discussions or other content* (17.5 %, $n = 1229$), and *translating text or audio into another language* (16.1 %, $n = 1133$). Fig. 2 uses a stacked bar format to show the distribution of helpfulness ratings across each task, allowing easy comparison of how widely used and how effective GenAI was perceived to be for various types of academic work.

More specific tasks that may relate to specific discipline areas such as creating games, software, or apps were also less used; however, the majority of the students who did use GenAI for these purposes found it helpful. When we look at the means and frequencies of the response choices, we see that students are overall very positive about all of the tasks, and find GenAI helpful or very helpful, with some students unsure,

Table 7
Discouraging factors in the use of GenAI.

Discouraging factors	N	Not at all (1)	A little (2)	A moderate amount (3)	A lot (4)	A great deal (5)	*M*	*SD*	Spearman's correlation between discouragements and frequency of use	
									Correlation Coefficient (r)	Sig.
I am worried about breaking my university's rules	8097	734 9.1 %	993 12.3 %	1306 16.1 %	1947 24.0 %	3117 38.5 %	3.71	1.33	−0.150**	<0.001
It can be inaccurate or make things up	8097	248 3.1 %	712 8.8 %	1622 20.0 %	2417 29.9 %	3098 38.3 %	3.91	1.10	−0.270**	<0.001
It can't do what I need it to do	8097	936 11.6 %	1917 23.7 %	2428 30.0 %	1557 19.2 %	1259 15.5 %	3.04	1.23	−0.198**	<0.001
I don't know how to use it confidently	8097	2141 26.4 %	2084 25.7 %	1823 22.5 %	1157 14.3 %	892 11.0 %	2.58	1.31	−0.251**	<0.001
I don't know what tools to use	8097	2313 28.6 %	2070 25.6 %	1761 21.7 %	1105 13.6 %	848 10.5 %	2.52	1.31	−0.234**	<0.001
I can't afford access to good GenAI tools	8097	2855 35.3 %	1636 20.2 %	1625 20.1 %	1083 13.4 %	898 11.1 %	2.45	1.37	−0.035**	.002
I don't have access to good GenAI tools	8097	2922 36.1 %	1762 21.8 %	1680 20.7 %	965 11.9 %	768 9.5 %	2.37	1.33	−0.094**	<0.001
I want to do it myself	8097	605 7.5 %	1099 13.6 %	1874 23.1 %	2011 24.8 %	2508 31.0 %	3.58	1.26	−0.408**	<0.001
I am worried about the privacy of my own data	8097	1627 20.1 %	1582 19.5 %	1601 19.8 %	1478 18.3 %	1809 22.3 %	3.03	1.44	−0.253**	<0.001
I have ethical concerns	8097	1359 16.8 %	1386 17.1 %	1678 20.7 %	1463 18.1 %	2211 27.3 %	3.22	1.44	−0.358**	<0.001

Note. ** Correlation is significant at the 0.01 level (2-tailed). The value of correlation coefficient within 0.1 - 0.29 indicates a weak relationship, within.3 - 0.49 indicates a moderate relationship, within 0.5 - 1 indicates a strong relationship. Data represents the number of students who answered this question.

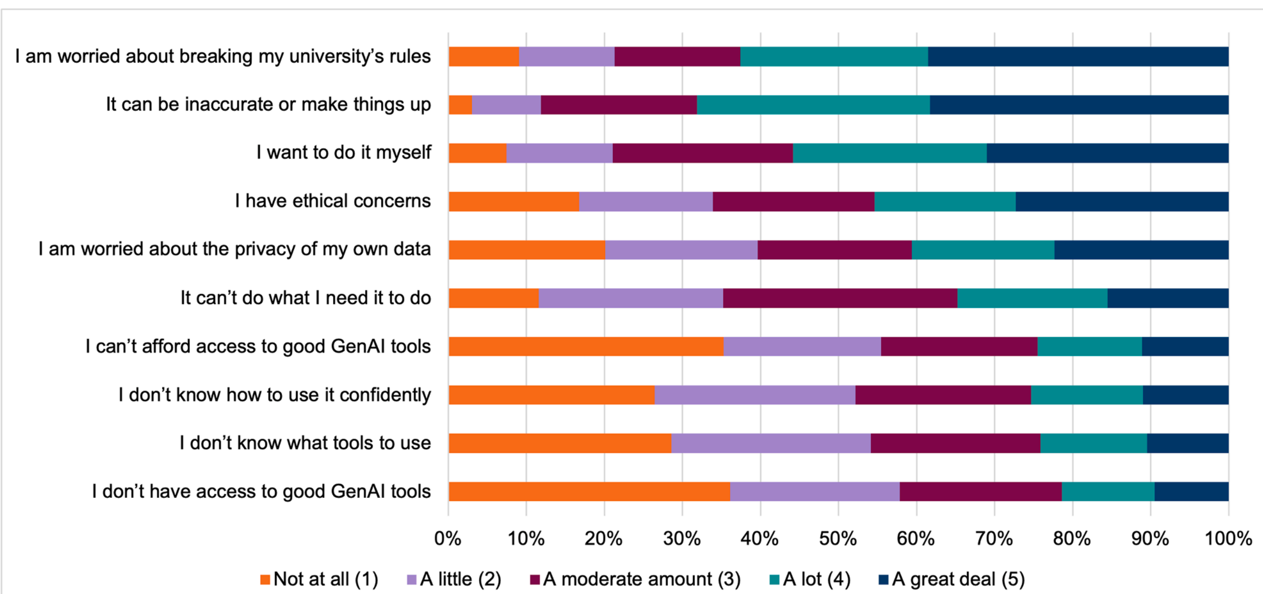

Fig. 4. Stacked bar chart of discouraging factors in the use of GenAI.

but very few reporting it to be unhelpful. All means reports were greater than 3.90 on a 5 point scale. Finally, only approximately 1 in 10 students (12.7 %, $n = 891$) reported using GenAI for *completing part or all of an assignment;* however, those that do are favourable towards its helpfulness ($M = 3.98$, $SD = 0.88$).

4.5. *Are students using GenAI to cheat on assessment?*

The survey asked students if they had "used GenAI to help them with an assessment when they were not supposed to?" We take such breaking of rules or expectations to indicate cheating. This allows for institutional wide framing of academic integrity rules as well as subject/unit level rules. Although we adopt this approach, we acknowledge that the term cheating can be defined in various ways [32]. As indicated in Table 5, most students (59.6 %, $n = 5059$) report that they have never used GenAI to cheat on assessment. However, 13.4 % ($n = 1139$) of students do so on a regular basis (half of the time or more).

4.6. *What motivates students to use GenAI for study?*

The findings indicate that students are motivated for a variety of reasons. As shown in Table 6, and visualised in Fig. 3, the most common reasons were that GenAI helps them overcome mental blocks ($M = 3.15$, $SD = 1.32$) and make tasks faster ($M = 3.10$, $SD = 1.32$) and easier ($M = 2.92$, $SD = 1.26$), while using GenAI for tasks beyond their own capabilities is less common ($M = 2.50$, $SD = 1.30$). All of the motivation items have a statistically significant correlation with increased frequency, with most having a moderate relationship and strong effect size (see Table 6). However, overcoming accessibility challenges has the weakest relationship ($r = 0.269$) with regards to frequency, although it should be noted that this item may be moderated by student perceptions of whether they have barriers that need overcoming.

4.7. What discourages students from using GenAI for study?

As shown in Table 7, and visualised in Fig. 4, concerns about accuracy ($M = 3.91$, $SD = 1.10$), and concerns about breaking university rules ($M = 3.71$, $SD = 1.33$) are the strongest reported deterrents to GenAI adoption. These are followed by the preference for independence ("do it myself") ($M = 3.58$, $SD = 1.26$) and ethical concerns ($M = 3.22$, $SD = 1.44$). A lack of skills and knowledge of GenAI tools ("don't know how to use it confidently" $M = 2.58$, $SD = 1.31$; "don't know what tools to use" $M = 2.52$, $SD = 1.31$), and access to GenAI tools ($M = 2.37$, $SD = 1.33$), including financial barriers ($M = 2.45$, $SD = 1.37$), are all reported by some students as discouraging factors. Indeed, all of the discouraging factors have a statistically significant correlation with less frequent use of GenAI for study purposes (see Table 7). However only the desire for independence ("do it myself") ($r = -0.408$) and ethical concerns ($r = -0.358$) have a moderately strong relationship with less frequent usage. This suggests that while all the other items are significant, including concerns about breaking university rules and inaccuracy, they are not strongly correlated with reduced usage.

5. Discussion

Our findings reveal a complex picture of student engagement with GenAI in higher education. The discussion that follows draws out five key themes from the data: awareness and adoption; trust and usage; use and usefulness; academic integrity; and finally, motivations and discouragements.

5.1. Awareness and adoption

Following the public release of ChatGPT, a number of studies explored students' awareness of GenAI tools, revealing varied levels of engagement. For example, A. Kelly et al. [6] reported that over 40 % of their sample (March 2023) exhibited minimal or no awareness. Given the rapid proliferation of GenAI, it is unsurprising that more recent studies, including our own, indicate not only increased awareness but also active usage among students. Our multi-institutional study, conducted between August and October 2024, found that 83.2 % of students had used GenAI tools for university study, with 44.5 % using it on a weekly or daily basis. Clearly, GenAI has become a common tool for most students. A closer analysis of the demographic breakdown reveals disparities that may warrant further exploration. Specifically, women and non-binary students as well as students with disability, health conditions, or who were neurodivergent were more likely to report not using GenAI. Understanding the reasons behind these variations will be an important agenda for future studies, as it could relate to potential issues of equity in access and adoption or conscious decisions to avoid GenAI use.

Considering the increasing adoption of GenAI, attending to the ways in which students learn about it also seems an important issue. Noteworthy, in this respect, is the predominance of self-directed learning approaches that were evident in our study. The most common method of learning about GenAI was through trial and error (65.7 %). This is followed by learning from internet searches (52.3 %), friends and other students (55.7 %), and from GenAI itself (43.1 %). In stark contrast, formal university resources such as workshops (12.5 %) and online resources (9.5 %) were utilized by only a small minority of students. These findings are consistent with previous research that identified informal, online, or peer-based avenues as primary sources of student awareness (A [6,13]). Our data suggests a further development of this trend: students are increasingly using GenAI itself rather than relying solely on informal or online resources to develop their skills in using GenAI tools.

The limited uptake of institutional resources raises important questions. It seems concerning that only around one in ten students in our study engaged with university-provided opportunities to learn about GenAI, which in turn raises questions about the relevance, accessibility, and timeliness of such offerings. There is a growing responsibility for universities to equip students with the ability to use GenAI effectively and ethically. Despite the limited uptake, it is interesting that 79.3 % of those who did access university workshops reported them as mostly/very helpful. It is possible that, in the survey period of August-October 2024, student awareness, workshop availability, or both, were limited. Further research is needed to evaluate the effectiveness of current GenAI education initiatives within higher education institutions. For example, in addition to strategies such as expanding traditional workshop offerings or creating more online guides, universities may also need to fundamentally rethink how they support emergent GenAI literacies. More effective approaches might include embedding contextualized GenAI guidance directly within assignment instructions, developing task-specific resources that align with common academic needs, leveraging peer learning networks, or scaffolding students to safely learn about GenAI through trial and error.

5.2. Trust and usage

Much of the educational technology discourse assumes a positive relationship between trust and use – that is, the more educators or students trust a technology, the more likely they are to adopt and use it (S [33,34]). For example, in their systematic review, Kelly et al. [34] found that trust, among other variables, "significantly and positively predicted behavioural intention, willingness, and use behaviour of AI across multiple industries" (p.1). In the context of higher education, Polyportis [8] found that increased trust was correlated with increased AI usage behaviour among students.. Similarly, trust is considered to be an important construct in human-AI interactions [35] and Nazaretsky et al. [33] argue for the importance of building educators' trust in AI-EdTech systems.

Our findings challenge the assumed linear relationship between trust and use. While we did see a moderate correlation ($r = 0.429$) between increased trust and increased usage, we also note, similar to Mustofa et al.'s [36] findings, that trust was not a determinant of use. While only 27.3 % of students reported trusting what GenAI generates, and just 3.2 % indicated strong trust, usage rates remain high: 83.2 % have used GenAI for university study, and 44.5 % report weekly or daily usage. At the same time, 66.6 % of students feel successful in using GenAI to meet their needs, suggesting a perception of personal competence even in the absence of deep trust in the tool's outputs.

This apparent contradiction suggests that students are making strategic, pragmatic decisions: using GenAI as a utility rather than a source of authoritative knowledge. In this sense, students may view GenAI not as a partner to be trusted, but as a tool to be managed: something to test, verify, and adapt. Such behaviour reflects a cautious form of engagement, where students maintain agency and scepticism, potentially as a way to mitigate risk while still gaining benefit.

It is also important to note that almost 20 % of students strongly distrust GenAI outputs. This group may reflect a cohort particularly concerned with accuracy, ethical implications, or the perceived lack of transparency in how GenAI generates content. Their perspectives may hold significant implications for how institutions frame GenAI in academic contexts: not just as a tool to adopt, but as a phenomenon that requires critical literacy. Indeed, engaging with AI outputs critically is key for good use because, as Shibani et al. [37] show, students often interact with generative AI in ways that are shallow and lack depth. The implication for educators and institutions is clear: scaffolding critical engagement by prompting students to interrogate, adapt, and justify AI outputs can help transform AI from a shortcut into a tool for deeper thinking and learning. Enabling this form of critical AI literacy among students can foster responsible and ethical use of AI for education [38].

Overall, our findings point to a more nuanced reality in which trust is not a binary condition but a dynamic state that coexists with perceptions of competence, context of use, and task specificity. For example, students may trust GenAI more in brainstorming or ideation contexts and less when accuracy or factual integrity is required. Future research should explore these conditional trust patterns and how students learn to calibrate their trust across different academic tasks.

5.3. Use and usefulness

Our findings reveal that students are employing GenAI for a broad range of academic tasks. The most commonly reported uses of GenAI were for improving writing (67.3 %), generating ideas and examples (64.4 %), summarising academic materials (54.3 %), learning how to do something (50.8 %), and getting feedback (49.7 %). These high-use categories suggest that students view GenAI primarily as a tool for enhancement and efficiency, supporting the development, organisation, and expression of academic work. A small number of studies have made similar observations, that GenAI is valued by students as a cognitive and creative support tool, helping students ideate, refine, error-check, and consolidate, rather than simply generate finished work (e.g., [9,15]). We provide a detailed analysis elsewhere of students' perceptions of feedback from GenAI versus teachers [39].

Less frequently used applications, such as generating creative media (5.2 %) or creating games, software, or apps (4.4 %), are likely tied to discipline-specific needs, such as digital design, media, or computer science. Their lower rates of use likely reflect the fact that fewer students engage in these types of tasks as part of their studies, but those students in specialised or creative academic contexts rated GenAI as useful.

Across all tasks, students reported consistently positive levels of perceived usefulness, with mean ratings exceeding 4 out of 5 in most categories. This suggests that GenAI is not only widely used, but also broadly valued as an academic aid. These findings support the notion that students are making strategic and pragmatic decisions about how and when to engage with GenAI. This task-oriented approach aligns with earlier research in which the perceived usefulness of GenAI for specific tasks were strong predictors of use (S [34,36]). An implication is that as institutions consider the role of GenAI in curricula, understanding where students find it most valuable can inform the development of more targeted guidance, skill-building initiatives, and ethical frameworks.

In the light of concerns around the inappropriate use of GenAI to write assignments, it is notable that in this survey, only 12.7 % of students reported using GenAI to complete part or all of an assignment. This suggests that while students are open to using GenAI for support and exploration, they are more reserved when it comes to direct assessment-related tasks, potentially indicating a degree of ethical awareness or uncertainty about boundaries. This interpretation is aligned with the findings of Johnston et al. [9] who found that students made a clear distinction between what they saw as acceptable uses of GenAI (for editing, understanding concepts, and error checking) and what they viewed as unacceptable (writing entire assignments).

5.4. Academic integrity

A sizeable proportion of students (40.4 %) reported using GenAI in violation of assessment policies. According to our findings, 13.4 % of students regularly use GenAI to help them with assessments when they are not supposed to (6.1 % "about half of the time", 5.4 % "mostly", 1.9 % "always"). A further 27 % reported using it "sometimes" for this purpose. This warrants careful attention, especially given the likely under-reporting from students on this sensitive question.

At first glance the frequency of misuse of GenAI in assessment appears to be in tension with the previously reported low percentage (12.7 %) of students who used GenAI to complete part or all of an assignment. However, Johnston et al.'s (2024) findings may offer some insight, showing that students distinguished the use of AI in the preparation and improvement of assessment from the use of AI to do the assessment. This raises a broader academic integrity question in the context of GenAI. We could interpret the data to suggest that while a relatively small proportion of students are using GenAI to complete their whole assignments, there is a larger proportion of students using GenAI to help them with assessment in other ways. Lund's et al. [40] study also noted that the majority of students saw the use of GenAI to write an assessment as a major misconduct, while smaller AI-assisted tasks were thought to be more acceptable. In contrast, Keuning et al. [21] observed an increase in the number of computer programming students who believed it was ethical to use AI to generate complete solutions for assessment without understanding the outputs at all. This perhaps highlights a challenge for institutions to consider how students interpret and navigate evolving norms [2]. For instance, some students may not view using GenAI for paraphrasing, idea generation, or content refinement as cheating, even when such use contradicts stated policy. Others may struggle to identify where ethical boundaries lie, particularly in the absence of clear guidance or consistent messaging from instructors.

These dynamics reflect a broader tension between existing university rules which are lagging in providing clearer guidance to students, and the capabilities of new technologies. As GenAI becomes more integrated into the fabric of everyday academic work, enforcement alone is unlikely to ensure integrity [16]. Rather, universities may need to focus on fostering a deeper understanding of why certain uses are considered inappropriate and how ethical engagement with AI can be supported through clearer policy, pedagogical design, and student education [7]. The sizeable group of students regularly using GenAI in breach of policy serves as a critical signal that integrity frameworks and supporting strategies must evolve alongside technology.

5.5. Motivations and discouragements

Our investigation into what motivates and discourages GenAI use reveals complex decision-making processes that often involve weighing immediate practical benefits against broader concerns. Among motivating factors, the most powerful drivers relate to productivity and workflow efficiency. This includes getting unstuck or overcoming blocks (44.2 % reporting "a lot" or "a great deal" of motivation), making tasks faster (43.7 %), and making things easier (34.9 %). Notably, motivations tied to process improvement appear more influential than those linked to academic outcomes. For instance, fewer students reported being strongly motivated by improving grades (17.1 %) or enhancing the quality of their work (26.3 %). This pattern suggests that GenAI is valued more for how it facilitates academic work than for its direct impact on final results.

Importantly, all motivation items showed statistically significant positive correlations with increased frequency of use, with the strongest effects associated with productivity-related drivers. One interpretation of these findings is that there may be a reinforcing cycle in effect: once students experience time-saving or problem-solving benefits from GenAI, they are more likely to incorporate it into their academic routines. These findings align with broader patterns identified in earlier sections, where GenAI is used as a flexible, task-specific support tool.

In contrast, our findings on discouraging factors present a more complicated picture. The strongest deterrents reported by students include concerns about accuracy and misinformation (68.2 % reporting "a lot" or "a great deal"), breaking university rules (62.5 %), and the desire to complete work independently (55.8 %). Yet despite the prevalence of these concerns, their correlation with reduced usage is surprisingly weak. Only the desire for independence ("I want to do it myself") and ethical concerns showed moderate negative correlations with frequency of use, while concerns about rule-breaking and accuracy, despite being widely held, showed weaker associations with reduced use.

This discrepancy between concern and behaviour challenges conventional assumptions underpinning AI-related academic policy. Deterrence-based approaches centred on rules, compliance, and enforcement may have limited influence if students continue to perceive GenAI as meaningfully useful in their workflow. Likewise, critiques that emphasise GenAI's inaccuracies may overlook the fact that students often use these tools critically and selectively, integrating them into broader learning strategies despite known limitations.

Taken together, these findings suggest that institutional responses to GenAI should move beyond messaging focused solely on risks or prohibitions. Instead, there is a need to understand and engage with the practical motivations that drive student use, and to embed clearer guidance and ethical framing within the contexts in which students are already finding GenAI valuable.

6. Limitations

This is a large-scale study drawn from four Australian institutions. However, given convenience sampling was used in the recruitment process, the data cannot be deemed to be representative of the institutions. Participants in this study are those who willingly took part which may have led to the nonresponse bias where the characteristics of students who completed the survey differ from those who did not respond. The survey was optional and therefore students with stronger views about GenAI may have been more inclined to answer the survey. We also note that Australian higher education may differ from other contexts that do not have similarly strong regulatory environments that have required institutions to address GenAI in teaching and assessment (see for e.g. [24,41]). Finally, this survey was completed August-October 2024 but GenAI tools have continued to grow in capability and availability, for both generic and specific applications (e.g., purposefully designed chatbots for learning contexts).

7. Conclusion

Our findings demonstrate that GenAI had rapidly become embedded in the academic practices of the majority of students surveyed, with over 80 % having used it for study-related tasks and nearly half using it regularly. Yet this widespread adoption is accompanied by complex patterns of trust, task-specific use, ethical ambiguity, and diverse motivations, suggesting that student engagement with GenAI is both highly pragmatic and context-sensitive.

Most students were not adopting GenAI uncritically. While trust in its outputs is relatively low, especially in tasks requiring factual precision, students report feeling competent in managing and applying GenAI to meet their academic needs. Their most frequent uses (editing writing, summarising content, and generating ideas) suggest that GenAI is primarily valued as a support tool for thinking, learning, and improving academic outputs, rather than for outsourcing academic responsibility. Usefulness, not blind reliance, appears to be the driving force behind sustained engagement.

Importantly, students appear to be navigating GenAI adoption largely through self-directed learning, with little reliance on institutional resources. This highlights both the initiative of students and a potential shortfall in university-led guidance. As GenAI continues to evolve, institutions must consider whether current resources and policies are keeping pace with student needs and experiences. Equity concerns, particularly for students less likely to engage with GenAI, such as women, non-binary, neurodivergent students (cf [42]), or those with health conditions, also demand closer attention.

Our findings on academic integrity suggest that while most students reported that they refrained from using GenAI in prohibited ways, a noteworthy proportion regularly engaged in behaviours that contravene university policies. This points to a pressing need for institutions to revisit how academic integrity is framed and communicated in a GenAI-enabled environment, how we equip students to use GenAI *mindfully*, and how assessment practices must evolve. In this light, policies that rely on deterrence or assume clear ethical boundaries may no longer be sufficient, especially as students' ethical reasoning appears more situational and task-specific.

Finally, the study reveals a set of powerful motivators that explain why students are turning to GenAI, such as speed, ease, and overcoming cognitive blocks. At the same time, common concerns about inaccuracy or institutional rules, while prevalent, do not appear to strongly deter usage. This disconnect between concern and behaviour underscores the limitations of awareness-raising alone. Institutions will need to engage more deeply with the real value students perceive in GenAI and develop responses that align with how, why, and where students are actually using these tools. Accordingly, in terms of policy, as noted earlier, institutions and educators need to frame GenAI as more than a tool, and help students acquire critical AI literacy for its responsible use in future contexts [37,38].

The rapid evolution of GenAI tools means that the specific platforms and capabilities will continue to change. However, the fundamental patterns identified here likely represent enduring features of how learners will navigate an increasingly AI-mediated educational landscape: that students hold productivity-oriented motivations, self-directed learning approaches, and sceptical-yet-practical engagement with these technologies. Understanding and responding to these patterns represents one of the greatest challenges and opportunities for higher education in the coming decade.

CRediT authorship contribution statement

Jennifer Chung: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Michael Henderson:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Christine Slade:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Yifei Liang:** Writing – review & editing, Formal analysis, Data curation. **Nicole Pepperell:** Writing – review & editing, Formal analysis, Conceptualization. **Thomas Corbin:** Writing – review & editing, Writing – original draft, Formal analysis. **Jack Walton:** Writing – review & editing, Writing – original draft, Investigation. **Alice Shihua Yu:** Formal analysis. **Margaret Bearman:** Writing – review & editing, Project administration, Methodology, Conceptualization. **Simon Buckingham Shum:** Writing – review & editing, Visualization, Project administration, Methodology, Conceptualization. **Tim Fawns:** Writing – review & editing, Project administration, Methodology, Conceptualization. **Trish McCluskey:** Writing – review & editing, Methodology, Conceptualization. **Jan McLean:** Writing – review & editing, Investigation. **Glenys Oberg:** Writing – review & editing. **Ari Seligmann:** Writing – review & editing, Methodology. **Antonette Shibani:** Writing – review & editing, Methodology. **Aneesha Bakharia:** Writing – review & editing. **Lisa-Angelique Lim:** Writing – review & editing, Methodology. **Kelly E. Matthews:** Writing – review & editing, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2026.100347.

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