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The GenAI divide among university students: A call for action ☆

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ABSTRACT

The rapid pace of technological change with generative artificial intelligence is accelerating much faster than our capacity to understand and regulate it. Higher education institutions have been firmly focused on the impacts of this innovation on academic integrity while grappling with unknown longer-term impacts on students' academic study and future work. This mixed method study aims to capture student perspectives on their self-reported understanding of GenAI and intentions to use GenAI for their academic study during the critical diffusion stage and policy vacuum. Through a survey with 194 university students, the study explored student's understanding, knowledge, experience and intended use of GenAI tools to support their academic study. The paper presents three distinct student profiles established through cluster analysis of measures of digital and AI literacy, which are then explored in-depth through presentation of qualitative items. Notably, the cluster profiles demonstrate variation across the profiles of novice, cautious and enthusiastic users and patterns related to their knowledge of ChatGPT and intended uses. The paper draws on digital divide empirical literature and explores the potential to repeat digital divides among groups of students based on their access, capabilities, and capacity to leverage these for educational advantage. We propose that building upon a vast existing body of educational research about digital literacy inequalities offers rich insights into the current problems facing education institutions, specifically, what role do universities play in supporting students to understand and harness GenAI, now and in their futures.

1. Introduction

Generative artificial intelligence (GenAI) is a popular term used in this paper to describe applications built on large language models (LLMs) such as GPT-4 that generate human-like text in response to a user prompt (United Nations Educational, Scientific and Cultural Organisation (UNESCO), 2023). While there is a history of inquiry into teaching, learning and assessment with artificial intelligence (AI) technologies, the fast pace of innovation and diffusion of GenAI technologies took higher education institutions (HEI) by surprise (Lodge et al., 2023). Globally, governments, regulators and institutes have grappled with how to mitigate GenAI risks to education in a context where technology is rapidly evolving. Responses have varied, but included banning GenAI, assessing needs for adapting existing frameworks, and urgently formulating new regulations (United Nations Educational, Scientific and Cultural Organisation (UNESCO), 2023). UNESCO provided guidance for AI in education and research advocating for a human-centered regulatory approach to AI in education to promote inclusion through access (i.e. the provision of high-quality, safe GenAI tools) and a focus on the protection of foundational skills in conjunction with the development of AI literacies (United Nations Educational, Scientific and Cultural Organisation (UNESCO), 2023). While in Australia, the national higher education regulator, Tertiary Education Quality and Standards Agency (TEQSA), commissioned a response to the impacts of GenAI on assessment with the intention to support HEI to reflect on impacts on teaching, learning and assessment (Tertiary Education Quality and Standards Agency (TEQSA), 2023).

Within the field of educational technology research, the risk-oriented response to GenAI is distinct from the usual rhetoric around technology-enhanced learning that has dominated approaches to diffusion.

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Educational technology research has long examined the adoption of technologies within educational institutions and how learners' access and use them for learning. Even the research on adoption of AI technologies in education has predominantly focused on the potential of AI to enhance aspects of education (Ifenthaler et al., 2024, Gibson et al., 2023). While institutional responses are unfolding and are relatively well documented, there is a paucity of research that explores the uptake and use of GenAI from the student perspective at this significant point in time. The current study aims to capture student perspectives on their self-reported understanding of GenAI and intentions to use GenAI for their academic study during the critical diffusion stage and policy vacuum. Specifically, the two research questions are 1) Which clusters can be identified with respect to students' knowledge and use of digital technologies and artificial intelligence? and 2) What is the link between the students' clusters and their intentions to use GenAI for their academic study, and the perceived benefits and limitations?

1.1. Background

In the beginning of 2023, HEI were faced with new advancements in GenAI technologies and what this would mean for the forthcoming academic year in the Southern hemisphere and the rest of the semester in the North. Universities in Australia, the United States, India, France, the United Kingdom, and Hong Kong reported taking active steps to limit or exclude students from using GenAI, with a large focus on the way this would impact assessment and the verification of achieving learning outcomes. As such, there was an urgent call for policies that acknowledged and provided guidance around ethical and appropriate uses in context. Yet much of this guidance specifically referred to what to avoid, or the consequences of use, rather than the affordances, benefits or approaches and support for teaching and students.

1.2. Student responses to the introduction of GenAI tools

While research has documented demands on learners including academic integrity (Moya et al., 2023; Playfoot et al., 2024), AI literacy (Ng et al., 2021), access (Johnston et al., 2024) and ethics (Lachheb et al., 2025), few studies have focused on capturing student perceptions and use GenAI in their academic studies. Importantly, emergent research examining student perspectives shows positive perceptions about the integration of GenAI in teaching and learning (Chan & Hu, 2023; Ng et al., 2021; Wang & Zhang, 2023). For example, in a survey study of 399 undergraduate and postgraduate students in Hong Kong students generally reported positive attitudes towards GenAI in teaching and learning (Chan & Hu, 2023). Despite this small body of emerging research, student perspectives have largely been missing from empirical work and current HEI policy development. One of the primary foci of research on university students has been to measure and conceptualize their knowledge or 'literacy' of this emerging technology (Lachheb et al., 2025).

1.3. Conceptualizations and measurements of digital literacy

An understanding of digital literacy and digital divides over time is particularly useful for understanding the ways students come to engage with emerging technologies like GenAI. To effectively access emerging digital technology, students draw on their digital literacy (Carter et al., 2020). Digital literacy broadly describes the knowledge, skills, and dispositions required to effectively use digital technologies. Operationalized measurements of digital literacy have been structured around skills, context, experience, and use (Eynon & Geniets, 2016), and self-efficacy, confidence, and motivation (Hatlevik et al., 2018; van Deursen et al., 2014). Generally, research shows that young people do not uniformly possess high levels of digital literacy. The question remains to what degree digital and AI-related knowledge and use can be associated with uptake.

Understanding students' GenAI use through a digital and/or AI literacy lens allows for consideration of foundational knowledge that a student must deploy to effectively engage with such tools. Moreover, such a lens supports an understanding of the ways that AI literacy may contribute to, or compound existing digital divides. In their review, Ng et al. (2021) found a variety of definitions of AI literacy. But most of the studies included in their review advocated that instead of knowing how to use AI, learners should learn about the underlying AI concepts and ethical concerns to use AI responsibly in their future careers. This is in line with the Long and Magerko (2020, p.2) definition: "AI literacy is a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace". The patterns of variations in AI and digital literacy have been referred to as digital inequalities or digital divides evident in a range of measures of digital literacy and digital divide research for over two decades (Carter et al., 2020; Corrin et al., 2019).

1.4. Digital divide and AI

The digital divide was initially used to describe differences in access to digital technologies (Warschauer & Matuchniak, 2010). This early research was concerned with the equalization of access to digital technologies. Beyond access, second level digital divides were concerned with differences between individual's effective access or the digital competencies required to effectively use digital technologies. Within this frame researchers investigated profiles of users to understand the ways that differences in digital competencies occur (cf. Tondeur et al., 2011). Warschauer and Matuchniak (2010) suggested a graduation instead of a divide between those who can use digital technologies to access, adapt and create knowledge and those who cannot. Clearly, access alone will not overcome inequity in use, understanding, and outcomes. According to these authors, the digital divide resides in the differential ability to use new digital technologies, like GenAI, to perform a variety of complex and contextual practices such as critically evaluate information, analyze and interpret data, collaborate with others in knowledge production, and communicate effectively to diverse audiences.

The body of digital divide literature suggests that emerging technologies further contribute to patterns of access and capabilities. Although research about the digital divide and AI is scarce, some researchers have begun exploring AI implications for the digital divide (e.g., Carter et al., 2020; Kitsara, 2022). To illustrate, a recent hermeneutic literature review presented the current state of the digital divide, developments in AI, and AI's potential impact on digital divides through three levels of the digital divide: access to AI (the first level divide), capabilities to use AI (the second-level divide), and the outcomes of AI engagement (the third level divide) (Carter et al., 2020). The authors draw on a body of digital divide research spanning over 60 years to conceptualize the digital divide in the age of AI and postulate how nature of GenAI itself may work to shape inequalities in AI access, capabilities, and benefits. The review calls for research to investigate the digital divide within the context of the emergence of GenAI.

Building on the extant body of digital literacy and digital divide literature, this paper aims to examine students' academic digital profiles through self-reported measures of digital and AI literacy to understand their intended uses of GenAI for academic study. The focus is not only on students' knowledge and usage of GenAI, but also on how this can be associated with their existing digital profile (cf. Vuorikari et al., 2022). Hence, in the current study, a person-centered approach is applied in which the students are regarded as dynamic systems of interwoven components (cf. Tondeur et al., 2021). While the variable-centered approach is concerned with information about the variables, its structure, stability and validity for an average person (Bergman & Wångby, 2014). To better understand the GenAI divide, person-centered approach seems important because each person is considered a functioning totality. In the next part, we further explain the goal and the method of the current study.

1.5. The current study

Understanding the digital profile of university students to support their use of AI in education presents a significant challenge, given the considerable diversity among the student population (cf. Tondeur et al., 2021). A crucial first step in identifying a potential digital divide is to gain insight into students' existing knowledge and usage of AI technologies. This study aims to contribute to that goal by exploring potential variations in students' academic digital profiles. Specifically, it examines the digital clusters of students based on their digital and AI-related knowledge and use. Accordingly, the first research question (RQ) guiding this study is:

RQ1: Which clusters can be identified with respect to students' knowledge and use of i) digital technologies and ii) artificial intelligence?

Secondly, the present study explores qualitatively more in-depth students' intentions to use GenAI in their current studies. This leads to the second research question:

RQ2: What is the link between the students' clusters identified in RQ1 and their intentions to use GenAI for their academic study, and the perceived benefits and limitations?

The mixed method analysis enabled both the identification of patterns in the student data (RQ1) and an exploration of whether students' perceptions aligned with the identified clusters, providing elaboration, illustration, and clarification through quotes from the open-ended responses.

2. Method and approach

2.1. Context of the study

The findings presented in this paper are illustrative of students at one university at a particular moment in time. Data were collected between March and April 2023 at a public university in Australia. At this time, students and teachers were beginning a new academic year only three months after ChatGPT had been widely released. As such, HEI in Australia, and internationally, were in a significant panic about how to address this new and unknown tool in light of academic integrity issues (e.g. Lodge et al., 2023). For the university in this study, there was no institutional guidance or policy to direct how GenAI could or could not be used in teaching and learning.

2.2. Sample

The study sample includes students across disciplines and years of study. Students were invited to complete an anonymous survey in their lectures. However, recruitment of students via subject lectures was challenging. Many coordinators declined the invitation to recruit students within their cohorts for fear of raising their awareness of ChatGPT. ChatGPT was overwhelmingly the predominant LLM at the time of data collection.

In total, 336 students were invited to participate early in the Australian academic year (March–April 2023). Of those students, 194 completed the full survey (overall 58 % response rate) with 146 students completing the open-ended response items. Data was collected over a two-week period within each subject, early in the semester, ensuring students had time to become familiar with the subject assessments, expectations of study, and develop intentions about how they would engage. Due to the anonymous nature of the exploratory survey minimal demographic data was collected. The sample included students across years of study (first year of undergraduate degree, 49.5 %; subsequent year of undergraduate degree, 30.4 %; postgraduate or higher degree level, 20.1 %) and faculties (Social Sciences, 56.2 %; Natural Sciences, 27.8 %; Humanities, 15.5 % and Business, 0.5 %).

2.3. Data collection instrument

The aim of the survey was to provide a snapshot in time. The survey was developed to capture students' knowledge, current use of digital technologies and AI, and their intended use of GenAI (specifically ChatGPT) in their academic study. The survey included Likert-type scales, and open-ended questions. Survey items presented in the results are outlined in Appendix A.

2.3.1. Measures of knowledge, use and confidence

A truth-based measure addressing students' digital literacy was created to capture their knowledge and use of digital technology (see Appendix A). The measure comprised four items addressing: knowledge and use of the technology (see Eynon & Geniets, 2016), and confidence in their own abilities (Hatlevik et al., 2018). These employed a four-point Likert-scale of truth statements (4 = "very true of me", 3 = "true of me", 2 = "somewhat true of me" and 1 = "not true of me"). Truth statements have been demonstrated to invite more neutral and objective responses compared to scales that may invoke evaluation or comparison to others (van Deursen et al., 2014). A four-point Likert-scale was chosen to remove the neutral option and require participants to choose whether the statement of true for them or not. Research has shown that scales remain valid whether they are 4-point, 5-point or 6-points (e.g. Adelson & McCoach, 2010).

Given the emergent nature of GenAI at the time of the study, the measure focused on AI, rather than specifically GenAI. This was intended to be more inclusive of a broader range of student understandings and experiences, given its early state of diffusion. This measure was designed based on the same principles as the digital literacy measure, using truth statements. It also addressed the use of AI in relation to their knowledge, use, and confidence.

2.3.2. Intentions to use ChatGPT for academic study, and perceived benefits and limitations

Three open items were designed to explore students' intentions to use ChatGPT in their current studies. Open-ended items were deemed most appropriate given the emergent nature of GenAI and the exploratory nature of the survey at this key point of innovation. At the time of data collection ChatGPT was the predominant GenAI tool, and thus the questions asked specifically related to students' intention to use, perceived benefits and limitations of ChatGPT in their current studies (see Appendix A). While reference to ChatGPT limited the scope of intended use, benefits, and limitations to one specific LLM, it also mitigated potential issues associated with students' understanding of terms such as GenAI or LLM.

2.3.3. Validity and reliability

Given that two new measures were used in the data collection, basic validity tests were conducted on the dataset. First, reliability testing showed that the full instrument measure was reliable ($N = 8$, $\alpha = 0.84$). For each literacy measure, reliability was over 80 %. The two literacy measures showed good internal consistency. The four items of the digital literacy measure showed strong significant correlations ($r = 0.366$ to 0.686, $p < .001$). For the AI literacy measure, the four items were also significantly and strongly correlated ($r = 0.614$ to 0.781, $p < .001$). The two scales were also correlated, as one may expect ($r = 0.351$, $p < .001$). In terms of content validity, 20 of the 149 open-ended responses were cross-checked with their responses on the two literacy measures. This triangulation demonstrated consistency of responses in the respondents. Therefore, given tests for validity and reliability, it could be reasonably believed that the data captured by the survey was sufficiently representative of the students' experiences. However, given the exploratory nature of the research and the limited capabilities of the measurement, results should be considered a preliminary step in this area of research.

2.4. Analysis

Analysis of the survey data was performed in two stages: cluster analysis and thematic analysis of the open-ended item responses.

2.4.1. Cluster analysis

The aim of the cluster analysis was to identify homogeneous groupings of participants ($N = 194$) based on their reported digital and AI literacy. This approach provides a way to group cases in a set of data within the nearest mean. This reduces observations into clusters, thus making comparisons easier. K-means clustering is particularly useful in identifying user profiles (Dalmaijer et al., 2022), in that individuals in the cluster are more similar than those from other clusters. Two scales on students' digital technology and AI literacy were used to perform the clustering. Importantly, cluster analysis is an interpretive quantitative procedure. There can be multiple cluster solutions, and the choice for a final cluster solution is often subjective.

Using SPSS 28, digital and AI literacy factors were calculated by summing the four items in each measure (minimum 0, maximum 12). As previously stated, correlation among the two factors was moderately strong and significant ($r = 0.351, p < .001$). Theoretically, to explore the two literacy scales, it is common in this type of research to first consider a 3-group solution, comprising: low, medium, and high reported levels of self-belief. As such, 2, 3 and 4-cluster solutions were tested. When compared to the 3-cluster solution, the 2-cluster solution obscured the important middle group and did not present a good representation of the sample. In the 4-cluster solution, the fourth cluster was too small and did not improve explanatory power. The 3-cluster solution was appropriate in that each cluster had a significant portion of members from the sample, with statistically significant variation between the profiles. The final distribution and scores can be seen in Table 1.

Mean scores for the three clusters were statistically different for both factor scores: digital technologies $F(2,191) = 211.4, p < .001$; and, AI $F(2,191) = 269.0, p < .001$. DT literacy accounted for 68.9 % variation among the clusters, while AI Literacy accounted for 73.8 %. However, Tukey HSD post hoc tests showed that High DT + High AI was not statistically different from Hight DT + Low AI ($p = .376$) This was a function of similar mean scores on DT. However, given the significant difference in the AI mean scores, these two profiles presented differently. This was internally validated through triangulation with the qualitative evidence and the three clusters were retained.

2.4.2. Qualitative analysis

Following this result, exploratory qualitative analysis was conducted through inductive coding on open items within the identified clusters. Of the 194 participants, 146 provided open-ended responses. Inductive analysis of the open-ended responses sought to explore themes relating to participant's knowledge of ChatGPT, specifically the benefits and limitations related to its use for study. Iterative coding was conducted by two researchers to establish and refine the coding framework relating to three broad categories: benefits, limitations, and intended use. After reaching 100 % agreement on a sample of 50 surveys, the coders double-blindly coded all items using NVivo. The inductive analysis identified a number of exploratory themes both across and within the clusters. Using mixed method analysis allowed for both identification of patterns within the participant data, but also exploratory analysis of participant practices (Miles et al., 2018) facilitating the exploratory analysis of the emerging phenomena. Comparison across the profiles demonstrated variation in their knowledge of benefits and limitations, and subsequently their intended use which are presented below.

3. Results

3.1. Student profiles

The cluster analysis results were three distinct literacy profiles (see Table 1). Thematic analysis of the 146 participants who provided qualitative open survey items demonstrated students' perceptions aligned with the identified clusters to establish three distinct profiles which will be detailed in this section. Student profiles with low and high levels of digital AI literacy will be presented first: novice users (low DT and low AI) and enthusiastic (high DT and high AI). Finally, the largest profile of cautious users is presented (high DT and low AI).

Thematic analysis of students' intentions to use ChatGPT in their current academic studies showed variation across the three profiles shown in Fig. 1. Enthusiastic users (who reported higher AI literacy) were the most likely to use ChatGPT in their academic studies, while novice and cautious users (students with lower AI literacy) were more likely to choose not to use it. Overall, students' use of ChatGPT for their studies was more conservative than popular opinion may have assumed at the time (Roe & Perkins, 2023).

Findings from open item descriptions of students' knowledge of and intentions to use ChatGPT are presented for each of the three cluster profiles in Table 2 and then detailed according to each profile in the following sections.

3.2. Novice users

Novice users were characterized by lower levels of both digital technology and AI literacy, as well as limited knowledge of benefits and limitations for the use of ChatGPT in their academic studies. Less than one quarter of novice users intended to use ChatGPT in their current studies.

3.2.1. Knowledge of ChatGPT

Students within this cluster provided short, non-technical, and at times unclear, responses to what they perceived as the benefits and limitations of the use of ChatGPT for their studies. From the 29 students within this cluster half perceived no benefits (n = 8), were unaware of any benefits (n = 4) or provided an unclear response ($n = 6$). 14 students were able to identify some benefits of ChatGPT. The benefits identified showcased potential uses of ChatGPT, but with limited detail or technical knowledge. This included using ChatGPT to generate writing for assessments ($n = 5$), as one student described: "Write ur assessment", answering questions ($n = 3$), e.g., "Equivalent to having someone there to ask questions as they arise", finding information ($n = 2$), ideation (n = 2) and writing summaries ($n = 1$).

Students within this cluster were able to identify more limitations than benefits suggesting a more tentative or emergent view of ChatGPT in their studies. Nineteen students ($n = 19$) identified some limitations,

Table 1
Cluster distribution and scores of the digital technology (DT) and AI literacy measures.*

	Low DT + Low AI Novice users $n = 41$ (21 %)				High DT + Low AI Cautious users $n = 96$ (49 %)				High DT + High AI Enthusiastic users $n = 57$ (29 %)			
	M	SD	Min	Max	M	SD	Min	Max	M	SD	Min	Max
Total score for digital literacy	7.07	1.46	3	9	11.26	0.94	9	12	11.53	1.34	5	12
Total score for AI literacy	1.63	1.79	0	7	2.72	1.64	0	5	8.81	1.97	6	12

* Final score on the two factors.

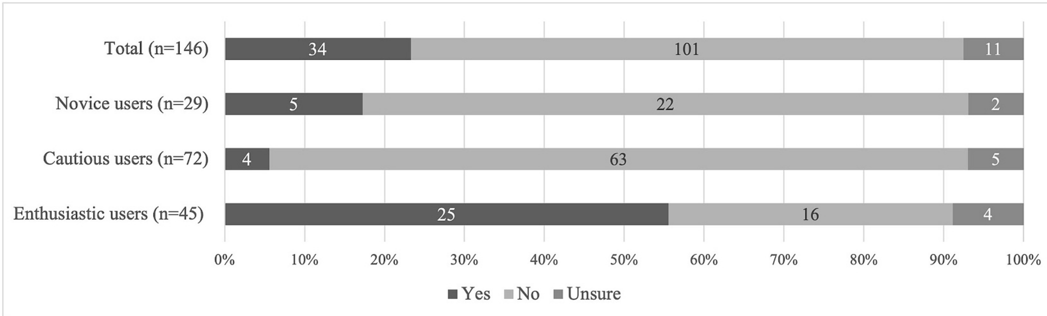

Fig. 1. Intention to use ChatGPT in current academic studies.

Table 2
Knowledge of benefits and limitations an intention to use ChatGPT by user profile.

	Novice users (n = 29)		Cautious users (n = 72)		Enthusiastic users (n = 45)	
	N	%	N	%	N	%
Knowledge of benefits						
No benefits	8	27.6 %	26	36.1 %	6	13.3 %
Unclear about the benefits	4	13.8 %	13	18.0 %	0	
Generate assessment work	5	17.2 %	0		5	11.1 %
Answering questions	3	10.3 %	5	6.9 %	7	15.6 %
Researching	2	6.9 %	0		5	11.1 %
Generating ideas	2	6.9 %	4	5.6 %	0	
Generating summaries	1	3.4 %	2	2.8 %	3	6.7 %
Writing support	0		9	12.5 %	0	
Enhance productivity or efficiency of tasks	0		0		9	20.0 %
Knowledge of limitations						
No limitations	0		0		4	8.9 %
Unclear about the limitations	6	20.7 %	13	18.0 %	0	
Risk or limitations associated with breaching university policy or academic integrity	5	17.2 %	9	12.5 %	8	17.7 %
Impacts on learning	2	6.9 %	7	9.7 %	3	6.7 %
Limitations based on functionality	3	10.3 %	5	6.9 %	5	11.1 %
Limitations associated with accuracy of responses generated	9	31.0 %	27	37.5 %	18	40.0 %
Limitations associated with the quality or relevance of responses generated	0		11	15.3 %	11	24.4 %
Intention to use ChatGPT	5	17.2 %	4	5.6 %	26	57.8 %
Monitoring understanding of subject content or process	2	6.9 %	1	1.3 %	12	26.7 %
Generate summaries of concepts/topics	2	6.9 %	1	1.3 %	5	11.1 %
Support with writing form or structure	1	3.4 %	0		4	8.9 %
Generating ideas or initial drafts	0		2	2.8 %	5	11.1 %
Researching	0		0		3	6.7 %
Writing and debugging code	0		0		6	13.3 %

six (n = 6) stated they did not know of any limitations associated with using GenAI for their studies, and three (n = 3) provided unclear responses. Limitations of ChatGPT included the inaccuracy of generated outputs (n = 7) or similarly, not being able to 'trust' the outputs (n = 2), and that ChatGPT was not capable of higher-level thinking required for university level writing (n = 3). Students also identified limitations associated with the use of ChatGPT, but not specifically its functionality, such as concerns associated with academic misconduct (n = 5), and that the use of ChatGPT would replace or limit their learning (n = 2).

3.2.2. *Intentions to use ChatGPT*

Three quarters of students within this cluster (n = 15) stated they would not use ChatGPT as part of their studies in the current semester. Five students described intended use of ChatGPT associated with addressing challenges in their studies such as to ask questions about subject content (n = 2) or advice about essay structure (n = 1); and to summarize concepts/topics (n = 2). Notably four students (n = 4) within this cluster had emotive responses towards the use of ChatGPT stating that they feared using it, or that it could not be trusted. For example: "I think it is very useful in many contexts, but I am just personally afraid of it."; "I don't really trust it to just formulate a correct and direct answer."

3.3. *Enthusiastic users*

By contrast enthusiastic users were those who reported high levels of digital and AI literacy. This cluster offered the most detailed and technical accounts of both benefits and limitations and intended uses of ChatGPT. This cluster of students was unsurprisingly the most likely to use ChatGPT in their academic study with more than half of the enthusiast students reporting intention to use during the current semester in uses focused on enhancing their learning.

3.3.1. *Knowledge of ChatGPT*

39 from 45 students described benefits associated with the use of ChatGPT, while six students (n = 6) stated they perceived no benefits to their studies. Benefits reported included general uses such as increased productivity (n = 9), for example: "ChatGPT removes repetitive tasks, freeing up time and increasing productivity, ultimately enhancing my academic experience." Benefits associated with specific uses such as asking questions (n = 7), summarization (n = 3), locating information (n = 2), and quick access to information (n = 3) were also described. This cluster also identified a range of more discipline specific uses including code generation, document formatting, data organization, and organizational support.

The limitations identified reflected their depth of knowledge about ChatGPT. 38 students identified limitations: four (n = 4) students stated there were no limitations, and four (n = 4) students provided no response. Students reported limitations associated with the accuracy but also the need to verify the outputs (n = 18), for example: "ChatGPT has limitations with higher-level reasoning, so I make sure to verify accuracy and use it as a supplement to my own critical thinking." Students also identified specific limitations related to the functionality of ChatGPT including the limited scope to generate only text-based responses (n = 5), its capability to provide responses relevant to academic tasks (n = 6), to generate output that shows higher-order thinking (n = 3) or personal opinions ($n = 2$). Students also identified academic integrity and university policy as limitations to its use in their studies ($n = 8$), and potential negative impacts upon their own learning (n = 3).

3.3.2. Intentions to use ChatGPT

Students within this cluster were most likely to use ChatGPT for their academic studies ($n = 26$). Intended uses included strategies associated with monitoring their understanding of content such as generating alternate explanations for complex or unfamiliar content (n = 8) and checking their own responses to assigned tasks (n = 2). Students also monitored their progress through writing support strategies focused on seeking feedback on grammatical features of their own writing (n = 2), or general writing support ($n = 1$). Students also intended to use ChatGPT for accessing or organizing learning content including summarizing readings or subject materials (n = 5) or locating relevant sources or information ($n = 3$). Other intended uses included generating initial ideas (n = 3) or drafts (n = 2) for their own writing, formatting a reference list (n = 1), asking questions (n = 2), or generating or debugging code ($n = 6$). Students' intentions to use it show the potential for using ChatGPT in productive ways. There were no reports of using ChatGPT to bypass learning, although, this is not to say that the students within this study may not have also used ChatGPT in ways that were less productive.

Students within this cluster who did not intend to use ChatGPT ($n = 15$) expressed their perspective that uses of ChatGPT was not germane to their academic studies ($n = 4$), would breach academic misconduct (n = 3), limit their learning (n = 1) or was unethical (n = 1). Six students (n = 6) cited no reason.

3.4. Cautious users

Cautious users also reported high levels of digital literacy, but unlike the enthusiastic users this cluster reported low AI literacy. Cautious users described more limitations than benefits associated with ChatGPT underscored by a general caution with using ChatGPT.

3.4.1. Knowledge of ChatGPT

Just over half of students within this cluster did not identify any benefits associated with the use of ChatGPT in their studies ($n = 41$). This included students who perceived no benefits ($n = 26$), who did not know of any benefits ($n = 13$), and two who did not respond (n = 2). The remaining 31 students described benefits but with less certainty than enthusiastic users highlighting their lack of knowledge. For example: "I see it as a good way to create questions on content, but other than that I am not sure of its ability as I haven't had much exposure to it yet, but I am keen to learn." These benefits included generating alternate explanations ($n = 5$), feedback or advice on structuring essays or writing (n = 5), getting feedback on their own writing (n = 4), generating ideas on a topic to inform their own research (n = 4), or generating summaries (n = 2).

The limitations reported highlight the cautious approach to using ChatGPT in their academic studies. 27 students identified the outputs generated by ChatGPT were typically unreliable or could not be trusted, for example, "not necessarily reliable, don't know where the information comes from or exactly how it generates answers" and "I don't trust it for research". Other limitations related to its non-use were concerns around academic misconduct policies ($n = 9$), and concerns that its use may limit their own learning ($n = 7$). Other concerns about the functionality of ChatGPT included low-quality or robotic generated text ($n = 6$), general descriptions of ChatGPT's limited functions (n = 5), limitations in generating responses relevant for academic studies (n = 5), and concerns about the lack of transparency of how ChatGPT works ($n = 3$). Seven students provided no response, and 13 more were not sure of any limitations.

3.4.2. Intentions to use ChatGPT

This cluster had the highest proportion of students who indicated they did not intend to use ChatGPT in their studies in the current semester ($n = 63$). Only four ($n = 4$) students in this cluster intended to use ChatGPT to work through questions assigned for their classwork ($n = 1$), to generate ideas for further research on a topic (n = 1), to generate a draft (n = 1) and to seek alternate explanations of unfamiliar topics (1).

For the students who were unsure or did not intend to use ChatGPT, some also acknowledged that they had no experience using ChatGPT or did not know about it ($n = 21$). Students also explained that they perceived no benefit ($n = 16$) or were concerned about risks associated with the university's academic integrity policy (n = 6) and thus reported not to use it. It was evident that a majority of students within this cluster had little to no experience using ChatGPT that likely shaped their decision not to use it for their studies.

4. Discussion

Digital divides have long been examined in education technology and public policy research. This body of research describes: i) the nature of digital divides as experienced by individuals, and ii) contributing factors (Lythreatis et al., 2022). In this exploratory study, we focus on the former, adopting a person-centred approach. The study results represent an important snapshot in time that depicts variation across different profiles of students' use and knowledge of GenAI. While the scope of the study findings is not intended to be generalised, the proceeding discussion is intended to prompt critical discourse on the implications of an emerging divide between those who have access and skills to benefit from GenAI and those who do not. At a time of great interest in understanding the impacts of GenAI, we emphasise the imperative role of educational institutions in bridging, rather than exacerbating, these emerging disparities.

Before discussing these findings, it is important to return to the risk-oriented context of higher education institutions' policies and management of applications of GenAI in which the study was conducted. Much of the initial rhetoric was focused on the potential of students using GenAI to cheat or mitigating risks associated with assessment design (Moya et al., 2023; Playfoot et al., 2024). This focus is still evidenced in institutional responses as universities work towards 'AI proof' policy and practice. Yet, the findings presented in this paper show that students' intentions to use GenAI (specifically ChatGPT) were perhaps not as widespread as the claims at the time and to some extent shaped by university policies. Research reporting on students' intentions to use GenAI was limited at the time of the publication of this paper; and thus, the findings reported here offer a historical account of student perspectives at the critical diffusion phase.

The aim of the study was to explore variations in students' academic digital profiles. Specifically, examining clusters of students based on their self-reported digital and AI literacy together with their perceptions of benefits, limitations, and intentions to use ChatGPT in their academic study. Three student profiles were identified demonstrating variation across students' self-reported digital and AI literacies while providing qualitative insight into how and why students intended to use ChatGPT in their studies.

The exploratory profiles of novice, enthusiastic and cautious users provide first of its kind empirical evidence about university students' differential GenAI engagement during the critical diffusion phase in Australian higher education. Importantly providing early insight into the ways students' differential AI literacy and use replicate historical digital inequalities. Notable patterns across the user profiles included variations in knowledge about ChatGPT reflective of students' self-reported AI literacies across the three profiles. Patterns were also observed in the intended uses of ChatGPT across the three profiles with enthusiast users citing uses that could enhance their learning or productivity, while novice users cited using ChatGPT to address challenges associated with their study or were less appropriate to incorporate into their academic study. Such patterns demonstrate that variations across digital and AI literacy of these user profiles may also be linked to uses of GenAI and differential benefits or outcomes. Finally, patterns were also observed in student perspectives of their access to ChatGPT for their academic studies. Enthusiastic users framed their perceptions of restrictive HEI policy as a limitation to their use, while the cautious and novice users were more likely to express concerns about breaching policy. The profiles show that while most students were generally acting with caution, students with higher levels of self-reported digital literacy and AI literacy were better placed to understand and use and benefit from GenAI within their studies. On the other hand, students with lower levels of self-reported digital literacy and AI literacy were largely uncertain (and at times fearful) about the technology, and its impacts upon their learning.

Like the well documented levels of the digital divide across access, capability and outcomes (Carter et al., 2020; Lythreatis et al., 2022), the distinct and varied profiles from this small sample of students illustrate similar patterns of access, understanding and intention to use and possibly benefit from GenAI in academic studies. Importantly, the student profiles support early assertions of scholars who highlight the ways that digital innovations perpetuate and extend to existing digital divides (Carter et al., 2020). Likewise, the profiles align with early studies of university students' perceived willingness to use GenAI and positive correlations between knowledge of AI and frequency of use (Chan & Hu, 2023). Significantly these patterns reflect the nature of existing capability divides and as the digital divide literature shows, this exacerbation may have differential flow-on effects to non-digital outcomes, such as learning (Corrin et al., 2019, United Nations Educational, Scientific and Cultural Organisation (UNESCO), 2023).

This student-centered understanding is critical in institutional responses to digital innovation. While the findings presented here show that higher levels of students' self-reported digital literacy did not necessarily result in early adoption of technologies, they do illustrate the differential impacts of a risk discourse generated by the institutional policy ban on GenAI on students. In practice, this may occur as 'enthusiastic' students are better positioned to leverage their existing access and capabilities to benefit from GenAI in their studies despite institutional policy, while 'cautious' and 'novice' students may experience compound disadvantage via the risk discourse emerging from institutional uncertainty and/or differential access and capabilities to harness the benefits of GenAI in their studies.

4.1. Implications

Higher education has a critical role to play in supporting *all* students to harness the benefits of GenAI technologies and ensuring a more even playing field. To achieve this means moving beyond a discourse of risk to student-centered institutional approaches (Dawson et al., 2023; Moya et al., 2023). Considering the body of research on digital literacy and divides (see for example Kitsara, 2022; Lythreatis et al., 2022) and the digital academic profiles presented in this study, Table 3 conceptualizes the ways university students may experience AI inequalities through their university study across three levels.

We offer this conceptual framework to inform future, focused, student-centered approaches to higher education policy, practice, and research, with an emphasis on:

- Equity in *access*, through the provision of high-quality, safe, and ethical GenAI applications for university study;
- A systematic focus on *capability* development, promoting understanding of both the benefits and limitations of GenAI as a core component of academic integrity, and integrating AI literacies alongside digital literacies in teaching, learning, and assessment across academic programs; and
- Targeted opportunities for critical reflection and evaluation of the *outcomes* of AI technology use in university study, everyday life, and future work.

Table 3
Conceptualization of GenAI use across three levels of the digital divide (adapted from Carter et al., 2020, italicized text shows links to student cluster profiles in this study).

Level	Ways students may experience GenAI inequalities
Access divide	● Personal access to GenAI including quality of application. e.g. free vs paid subscriptions ● *Student access to GenAI including availability of quality access through institutional access, policy and culture* ● *Personal motivation to access or not associated with value, perceptions, policy settings, articulated connections to future work and lives*
Capability divide	● *Student understanding of the nature of GenAI* ● *Student understanding and use of GenAI* ● *Student understanding and beliefs about appropriate uses of Gen AI for different contexts/purposes* ● *Student capability to use GenAI tools for their study and future work.* ● Student capability to connect with networks of resources to support their use of GenAI for their study and future work ● *Exposure and opportunities for the contextual development of digital literacy and AI literacy with content knowledge*
Outcome divide	● Student translation of AI access and capabilities for benefit in university study and future work opportunities. e.g. increases in efficiency in developing understanding and outcomes of assessment results

4.2. Limitations

It is important to acknowledge the limitations of this study. Firstly, the data was collected at a pivotal period during the first teaching session after ChatGPT had been widely released and at a time when the initial institutional response was to ban its use within HEI. Due to this ban, student demographic data was not collected to ensure students were comfortable in participating in the study and that students using ChatGPT against policy could not be identified in accordance with ethics approval. We acknowledge this restrictive approach may have impacted students' comfort in reporting on their true intentions to deploy GenAI in their study. However, the anonymity of the survey and the diverse and rich open-ended responses suggest that student reports depict an honest account of intentions. In addition, the mixed method survey provided the most appropriate format in which to collect timely data capturing students digital/AI literacy and intentions at a historically significant moment. We also recognize that using self-reported measures lacks an objective assessment of both students' prior exposure to GenAI, and a genuine measure of the AI literacy at a time when students had no reference frameworks or institutional guidance. Further, the self-reported digital and AI literacy measures used serve as a preliminary step in this area of research.

The exploratory profiles presented were generated from cluster analysis to reveal patterns within the data. While cluster analysis has limitations associated with difficulty in determining whether clustering has produced meaningful results, the point in time clusters and open-ended responses illustrate the ways that the diffusion of AI technologies in HE aligns with established scholarly understandings of digital divides. As Dalmaijer et al. (2022) suggest, the best pragmatic approach is to investigate when cluster analysis can or cannot help to identify subgroups in a dataset. We invite future research that explores a range of individual, contextual, institutional and demographic factors in relationship with the patterns of digital and AI literacy identified in the cluster structures presented this study.

5. Conclusion

The findings presented in this paper demonstrate patterns of AI literacy and GenAI use that reflect existing digital divides at a time of rapid technological diffusion. As data was collected during the early adoption phase of GenAI in higher education when policies and guidelines were limited, this study provides a valuable historical reference point for future evaluations of student use of technology. Through drawing on the digital divide literature, we warn how this exacerbation may have differential flow-on effects to non-digital outcomes, such as learning, everyday life and future work. As technology continues to evolve and institutions change at a slower rate, there is ongoing need for critical discussion and empirical research that builds upon existing empirical work to inform institutional approaches to innovation that are student-centered and support students to understand and harness the use of technological innovations such as GenAI, now and in their futures.

CRediT authorship contribution statement

Karley Beckman: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tiffani Apps:** Conceptualization, Writing – review & editing, Writing – original draft, Formal analysis. **Sarah Katherine Howard:** Writing – original draft, Formal analysis, Conceptualization. **Claire Rogerson:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Ann Rogerson:** Writing – review & editing, Conceptualization. **Jo Tondeur:** Writing – original draft, 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.

We confirm that this manuscript has been submitted solely to *The Internet and Higher Education* and that it is not published, in press, or submitted elsewhere.

We confirm that all the research meets the ethical guidelines, including adherence to the legal requirements of the study country.

The authors acknowledge that we have seen, read, and understood the journal's guidelines on copyright.

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Appendix A. Relevant survey items

Background information

- Year of study (checkbox). Options: 1st year of my degree; 2nd, 3rd, or 4th year of study at uni; Postgraduate study; Higher degree research study
- Field of study (checkbox). Social Sciences; Natural sciences; Humanities; Business

Measures of digital technology and AI knowledge and use

- Tell us about your use of digital technologies by responding to the following statements: Likert scale (4 = "very true of me", 3 = "true of me", 2 = "somewhat true of me" and 1 = "not true of me").
  o I regularly use digital technologies
  o I have a good understanding of digital technologies
  o I am confident using digital technologies in my everyday life
  o I am confident using digital technologies (e.g. Word, Google, etc.) in my study
- Tell us about your use of digital technologies by responding to the following statements: Likert scale (4 = "very true of me", 3 = "true of me", 2 = "somewhat true of me" and 1 = "not true of me").
  o I regularly use AI technologies
  o I have a good understanding of AI technologies
  o I am confident using AI technologies in my everyday life
  o I am confident using AI technologies (e.g. Grammarly, ChatGPT, etc.) in my study.

Intended use in academic study

- Do you intend to use ChatGPT this session? If so, describe how you will use it.
- What do you see as the benefits of using a tool like ChatGPT in your studies?
- What are the limitations of using a tool like ChatGPT in your studies?

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