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Disciplinary differences in undergraduate students' engagement with generative artificial intelligence

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Abstract

The rapid development of generative artificial intelligence (GenAI) technologies has sparked widespread discussions about their potential applications in higher education. However, little is known about how students from various disciplines engage with GenAI tools. This study explores undergraduate students' GenAI knowledge, usage intentions, and task-specific engagement across academic disciplines. Using a disciplinary categorization framework, we examine how the hard/soft and pure/applied dimensions relate to students' interactions with GenAI. We surveyed 193 undergraduates from diverse disciplines at a university in Singapore. The questionnaire assessed students' GenAI knowledge, usage intentions, and engagement with GenAI for cognitive and routine tasks against their disciplinary background. The results indicate substantial disciplinary disparities in the level of engagement of students with GenAI. Compared to pure fields, applied fields (both hard and soft) consistently exhibit higher levels of GenAI knowledge and utilization intentions. Furthermore, the engagement of GenAI in routine tasks is relatively consistent across disciplines; however, there are substantial disparities in cognitive tasks, with applied fields exhibiting higher engagement. These results suggest that the practical orientation of applied fields drives GenAI adoption and utilization in academic settings. The study emphasizes considering disciplinary differences to better integrate GenAI into higher education and calls for tailored approaches that align with each field's unique epistemological and methodological traditions to balance GenAI's practical benefits with the preservation of core disciplinary knowledge and skills.

Keywords: Generative artificial intelligence, Undergraduate students, Academic disciplines, Technology adoption, Task engagement

Introduction

The rapid development of advanced generative artificial intelligence (GenAI) tools, such as ChatGPT, has generated both excitement and concern in higher education (Rawas, 2024). These tools, which are capable of generating human-like text and engaging in complicated conversations, represent a substantial improvement over traditional digital technologies in educational settings (Chan & Hu, 2023). Recent studies have explored the potential applications of ChatGPT in various domains, including research assistance, idea generation, writing support, and specific fields such as physics education, medical writing, surgical practice, and healthcare communications (Berg, 2023; Bhattacharya et al., 2023; Bisdas et al., 2021; Chan & Hu, 2023; Eggmann et al., 2023; Kitamura, 2023; Liang et al., 2023). However, the swift adoption of GenAI in higher education has also raised concerns regarding the nature of learning, academic integrity, and the evolving roles of educators (Adiguzel et al., 2023; Baidoo-Anu & Owusu Ansah, 2023; Harrer, 2023; Warschauer et al., 2023). Tlili et al. (2023) conducted a user experience study to uncover users' perceptions of ChatGPT in education, emphasizing the need for guidelines to ensure its safe and responsible integration into educational settings.

GenAI's advanced natural language processing, dialogue capabilities, and adaptability to various tasks differentiate it from earlier digital tools (Bahroun et al., 2023), necessitating a closer examination of its integration into the learning process. Recent research has begun to investigate students' general perceptions towards GenAI and its potential effects, with studies finding generally positive attitudes but also concerns regarding accuracy, privacy, and ethical considerations (Chan & Hu, 2023; Sullivan et al., 2023). However, these general perceptions may not fully capture the nuanced ways in which students from different background engage with GenAI. As GenAI becomes more prevalent in educational settings, it is crucial to consider how its impact may vary across disciplines and tasks, each with its unique characteristics and requirements.

Disciplinary cultures significantly influence how students perceive and engage with AI technologies. Empirical evidence reveals clear differences in AI adoption across disciplines, with fields more aligned with technology, such as engineering, natural sciences, and information sciences, showing higher engagement compared to arts, humanities, and social sciences (Elshaer et al., 2024; Gray, 2024; Raman et al., 2024; Stöhr et al., 2024). These disciplinary differences are rooted in the distinct concepts, inquiry methods, and norms that shape students' professional identities (Starkey et al., 2023). While these studies highlight the importance of considering disciplinary differences in students' engagement with GenAI, they do not fully address how disciplines shape students' use of these tools at the task level—an important research gap that requires further investigation.

Task nature is another crucial factor to consider when examining the impact of AI in higher education. The influence of AI on the labour market predominantly occurs at the task level, with tasks requiring lower cognitive capabilities being more susceptible to AI replacement compared to those demanding complex analytical skills or emotional intelligence (Huang & Rust, 2018). Studying AI's impact at the task level is essential for higher education institutions to identify which skills and tasks should be prioritized in curricula to prepare students for an AI-integrated workforce. Moreover, the ethical considerations associated with AI use vary depending on the nature of the tasks, with more fundamental tasks like designing research experiments and peer review raising greater concerns compared to routine tasks like language editing and data analysis (Andersen et al., 2024; Eaton, 2023; Skulmowski, 2024). As formal academic norms for AI use are still developing, clear ethical guidelines and policies are needed to ensure responsible and appropriate use of AI in educational settings.

Therefore, the primary objective of this study is to investigate how the characteristics of academic disciplines—categorized based on Biglan's (1973) model— shape undergraduate students' engagement with GenAI, including knowledge, usage, and different task types (cognitive and routine). This research seeks to extend the literature by providing a discipline-sensitive analysis of GenAI engagement and by identifying the task-specific impacts of AI technologies.

Specifically, for the academic disciplines, we use Biglan's (1973) model to categorize three dimensions—life system focus (life vs. non-life), applicability (pure vs. applied), and paradigmatic development (hard vs. soft)—to better understand the variations among academic fields. Various academic disciplines exhibit distinct cultural, epistemological, and structural attributes that influence how students approach learning (Becher & Trowler, 2001; Biglan, 1973) and may potentially interact with AI tools in diverse ways. This study aims to examine the engagement with AI across academic fields. Specifically, we focus on the following research question: How does the engagement with GenAI vary according to the nature of academic fields (pure vs. applied) and the type of academic fields (soft vs hard)?

We consider three aspects regarding the engagement with AI: AI literacy, AI usage (intention and actual usage), and usage in different tasks (cognitive and routine work). Cognitive tasks require significant mental effort and critical thinking, while routine tasks involve repetitive or procedural activities (Koehler & Sauermann, 2023). This distinction is particularly relevant in the context of AI adoption, as previous research suggests that AI tools may impact these task types differently, with potentially more transformative effects on routine tasks (Koehler & Sauermann, 2024; Margaryan et al., 2011). Our study explores how disciplinary differences shape GenAI use for these different types of academic work.

To investigate these questions, we conducted a survey study at a university in Singapore, employing a questionnaire with close-ended, open-ended, and Likert scale questions. The questionnaire assessed students' AI knowledge, usage intentions, and engagement with AI for different types of tasks across academic disciplines. We analysed the data using correlation analysis with the chi-square test to examine the relationships between academic discipline characteristics and various dimensions of GenAI engagement.

Our study contributes to the understanding of GenAI in higher education in several ways. Theoretically, we advance the knowledge of disciplinary differences in GenAI engagement by integrating the framework of disciplinary cultures with the concept of task-based automation. By investigating the influence of both disciplinary characteristics and task types on students' AI adoption and use, this research provides a comprehensive view of the contextual factors shaping AI engagement in academia. Practically, our findings offer guidance for developing discipline-specific AI policies and practices in higher education. By identifying AI engagement patterns across academic fields and task types, the results can inform targeted interventions and support strategies tailored to each discipline's unique needs. Furthermore, the insights into task-level engagement can help institutions prioritize the development of AI-related competencies that complement AI capabilities, preparing students for an AI-integrated workforce.

Literature review

Biglan's (1973) study on subject matter characteristics provides a framework for understanding disciplinary differences. Academic disciplines vary in practical applications (pure vs. applied), paradigmatic structures (hard vs. soft), and focus on life systems. These variations impact faculty social connectedness, commitment to teaching and research, and scholarly output (Biglan, 1973). Clark (1986) further posits that disciplines constitute the fundamental organizational structure of higher education, parallel to academic institutions. Each intellectual cluster contains distinct disciplines with professional communities that share a culture, history, and common practices (Becher, 1994). These shared attributes foster a sense of belonging and loyalty among community members (Healey, 2000). Undergraduate education plays a key role in transmitting these disciplinary cultures, as students adopt the concepts, inquiry methods, and norms of their respective fields, shaping their professional identity (Starkey et al., 2023).

These disciplinary differences extend to the adoption and integration of new technologies. Walsh and Bayma's (1996) study on computer network use across scientific disciplines found that fields with unified paradigms and geographically dispersed but highly interdependent work, such as mathematics and particle physics, adopted computer-mediated communication (CMC) more extensively than fields with autonomous local groups, like experimental biology and chemistry. Additionally, they found that market orientation influenced CMC use, with more market-oriented fields like chemistry and biology limiting use to formal channels (Walsh & Bayma, 1996). Their findings suggest that the adoption and integration of GenAI may follow similar patterns, with more paradigmatically unified, market-oriented, and collaborative fields potentially being quicker to adopt and integrate these tools into their research practices.

Empirical evidence demonstrates clear disciplinary differences in AI adoption. Gray (2024) found a significant rise in publications using Large Language Models (LLMs) in engineering and natural sciences, indicating greater AI integration in these fields. A survey of Swedish universities showed engineering students had the highest positive engagement with chatbots, while humanities and medicine students had the lowest (Stöhr et al., 2024). Elshaer et al. (2024) revealed that social science students are more influenced by social factors in ChatGPT adoption compared to applied sciences students. Raman et al. (2024) found that information and computing sciences, along with biomedical and clinical sciences, demonstrate the highest engagement with ChatGPT, driven by perceived advantages like ease of use and compatibility with educational practices. In contrast, fields less aligned with technology, such as arts and social sciences, show lower engagement, with ethical concerns playing a larger role in adoption decisions.

Moreover, different disciplines operate under distinct epistemological paradigms that determine their focus and methodologies (Becher & Trowler, 2001; Gašević et al., 2014), potentially influencing how they integrate AI concepts, including GenAI. Dwivedi et al., (2021) found that computer science and engineering, with their emphasis on quantifiable and computational knowledge, tend to align more naturally with AI integration. In contrast, humanities and social sciences, which prioritize understanding human experience and qualitative insights, may face challenges in AI adoption due to epistemological differences.

This epistemological divergence can lead to varying levels of AI literacy across disciplines. Kember and Leung (2011) suggests that students in positivist fields like computer science and engineering typically exhibit higher technological literacy due to their curricula, which may extend to AI knowledge. By contrast, McChesney and Aldridge (2019) found that students in interpretivist disciplines often have less exposure to advanced computational technologies, potentially affecting their AI literacy and preparedness.

These disciplinary differences in epistemology, methodology, and AI exposure are likely to manifest in students' engagement with and utilization of AI technologies. As such, we expect to observe distinct patterns of AI usage and literacy across various academic fields. Therefore, we propose:

H1 There are significant disciplinary differences in AI knowledge and usage among university students.

H2 Students in applied fields (both hard and soft) tend to have more AI knowledge and usage intention compared to students in pure fields.

The application of AI in academic tasks exhibits variability across disciplines and is contingent upon the nature of the task itself. The task-technology-fit (TTF) model suggests that technology adoption and impact depend on the alignment between the technology's capabilities and user's tasks (Wu & Chen, 2017). Autor et al. (2003) distinguish between routine and non-routine tasks, as well as manual and cognitive tasks, arguing that computers can substitute for workers in routine tasks but complement workers in non-routine problem-solving and complex communication tasks. Margaryan et al. (2011) also found that students' use of technology for higher-order tasks is more variable across disciplines than routine information management.

Frey and Osborne (2017) further refine this distinction, differentiating between tasks susceptible to computerization (routine tasks) and those not (non-routine tasks), particularly tasks requiring creativity, problem-solving, and social intelligence. Similarly, Koehler and Sauermann (2024) categorized tasks into cognitive work, requiring significant mental effort and critical thinking, and routine work, involving repetitive or procedural activities. They suggest AI tools impact these task types differently, with potentially more transformative effects on routine tasks.

Routine tasks, which are well-defined, repetitive, and structured, remain consistent across different fields of study (Autor et al., 2003) and can be easily standardized and automated due to their predictability. AI tools designed for these tasks often fit well across disciplines (Frey & Osborne, 2017) because the tasks themselves exhibit high similarity across different fields. Chan and Hu (2023) found that most undergraduates from different disciplines perceived GenAI as a valuable tool with numerous benefits, primarily because it helps with formatting, information retrieval, and gathering citations, thereby improving efficiency (Popenici & Kerr, 2017). Moreover, AI capabilities align well with these structured tasks, excelling at processing repetitive, rule-based operations, reducing the cognitive load on students, and allowing them to focus on more complex and creative aspects of their work (Scherer et al., 2019).

In contrast, cognitive tasks are often complex, domain-specific, and require specialized knowledge (Gašević et al., 2014). GenAI's role in these tasks is more supportive and augmentative than fully automative, and AI tools designed for these tasks may vary in their effectiveness across disciplines. This variation can be explained by several factors. First, cognitive tasks differ significantly between disciplines, resulting in low similarity (Neumann, 2001). The diverse cognitive demands and methodologies inherent in each field (Biglan, 1973) lead to varying AI tool requirements and applications. For example, the humanities and social sciences prioritize critical thinking and qualitative analysis, and may use AI for textual analysis, qualitative data interpretation, and creative content generation. By contrast, engineering and sciences emphasize quantitative analysis and empirical research, and often involve tasks that benefit from AI's analytical and computational capabilities. These fundamental differences shape how AI tools are integrated into academic practices, reflecting each discipline's distinct needs and priorities.

Given these disciplinary variations in task types and AI applications, we expect to observe differences in how students across various fields engage with AI for different kinds of academic work. Based on the literature review, we propose the following hypotheses:

H3 The use of AI for cognitive tasks varies significantly across disciplines.

H4 The use of AI for routine tasks is more uniform across disciplines.

Methodology

This study investigates patterns of GenAI engagement across academic disciplines at a university in Singapore, targeting the undergraduate population. The research design was informed by a two-stage preliminary process. We conducted a Focus Group Discussion (FGD) with ten undergraduates from November to December 2023, who were selected through quota sampling to ensure a diverse representation across academic disciplines and study levels. Our research focus and questionnaire design were influenced by the findings obtained from the FGD. We conducted pilot testing with 30 undergraduates to further refine the questionnaire, with an emphasis on the coherence and clarity of the queries.

The finalized questionnaire was administered via Google Forms from December 2023 to February 2024. This platform was chosen to ensure anonymity and facilitate wide-reaching data collection, crucial for eliciting truthful responses to sensitive questions about GenAI usage (Tourangeau & Yan, 2007). The top 100 responses were offered a $10 voucher as an incentive to increase participation rates, and convenience and snowball sampling methods were implemented. A response rate of 74.2% was achieved by receiving 193 responses from 260 disseminated questionnaires.

The questionnaire employed a combination of closed-ended, open-ended, and Likert scale questions to collect both quantitative and qualitative data. It was divided into two primary sections: (1) Demographic Characteristics: Evaluating the study level, academic discipline, and awareness and knowledge of GenAI of students; (2) Usage of GenAI: Investigating the types of GenAI used, academic tasks that involve GenAI (open-questions), and the reasons for use or non-use (open-questions). Appendix A contains the entire questionnaire.

We use three variables to measure GenAI engagement. The first variable is AI knowledge *KnowAI_dummy*—a binary variable indicating the respondent's self-reported knowledge of AI, with a value of 1 indicating knowledge about AI and 0 indicating a lack of knowledge. The second variable *UseAI_ordered* is an ordered variable representing the extent of AI usage. This variable is coded on a three-point scale: where 1 denotes no intention to use AI, 2 indicates an intention to use AI but not currently doing so, and 3 represents active AI usage. The third variable is the specific research tasks that respondents use ChatGPT for. To facilitate the analysis and align with existing theoretical frameworks (Autor et al., 2003; Frey & Osborne, 2017; Koehler & Sauermann, 2024; Margaryan et al., 2011), we categorized these tasks into two broad types: cognitive tasks, which involve complex activities requiring higher-order thinking skills, and routine tasks, which encompass repetitive or procedural activities.

To code the third variable, two researchers independently reviewed each response to the survey question "For what types of academic tasks do you use GenAI for?" and categorized the mentioned tasks as either cognitive or routine (Table 1). Cognitive tasks included research assistance, brainstorming and idea generation, complex homework assistance, substantive writing and editing support (beyond grammar correction), and advanced coding tasks. By contrast, routine tasks include more procedural activities such as learning reinforcement, quick reference and fact-checking, grammar correction, paraphrasing, and language translation. To ensure inter-rater reliability and mitigate subjective interpretation, a third researcher was consulted in cases of disagreement between the two coders.

Based on the categorization of tasks as either cognitive or routine, we created two dummy variables: *Cognitive_task* and *Routine_task.* These variables indicate whether the

Table 1 Categorization of academic tasks using GenAI

Categorization	Items	Example responses
Cognitive tasks	Research assistance	'Background of research'
		'Literature reviews'
		'Data analysis'
	Brainstorming and idea generation	'Generating ideas for projects'
	Homework assistance (depending on the complexity of the questions)	'When unable to solve questions'
		'Complex problem-solving'
	Writing and editing support (beyond grammar correction)	'Structure and content feedback'
		'Advanced editing'
	Coding assistance (depending on task complexity)	'Writing and debugging code'
		'Complex programming tasks'
Routine tasks	Learning reinforcement	'Practicing problems'
	Quick reference and fact-checking	'Explaining concepts'
		'Checking facts'
	Writing and editing support (grammar correction and paraphrasing)	'Grammar correction'
		'paraphrasing'
	Language translation	'Translating text from one language to another'

respondent uses AI for cognitive tasks (1 = yes, 0 = no) or routine tasks (1 = yes, 0 = no), respectively.

For the classification of academic disciplines, we adapted Biglan's (1973) model, focusing on two key dimensions: Applicability (Pure/Applied) and Paradigmatic Development (Hard/Soft). The life/non-life dimension was not included due to the scope of our sample. Hard disciplines (e.g., science, engineering) investigate objective phenomena using established methodologies with high consensus on fundamental principles (Biglan, 1973). In contrast, soft disciplines (e.g., humanities, social sciences) study human-related phenomena using diverse theoretical approaches, with less consensus on core theories. The pure-applied dimension distinguishes between disciplines emphasizing theoretical explorations and those focusing on practical applications and real-world problem-solving.

Applying this adapted framework to our survey sample resulted in four distinct categories (Fig. 1):

- Hard-Pure (HP): the College of Science,
- Hard-Applied (HA): the College of Engineering,
- Soft-Pure (SP): the College of Humanities, Arts, and Social Sciences
- Soft-Applied (SA): the Business School.

We encoded these classifications into several variables. The variable *Category* defines the discipline characteristics: 1 for Hard and Applied (Engineering), 2 for Soft and Pure (Arts, Social Sciences), 3 for Hard and Pure (Science), 4 for Soft and Applied (Business). We also created two binary variables *pure_applied* (0 for Pure disciplines, 1 for Applied disciplines) and *soft_hard* (0 for Soft disciplines, 1 for Hard disciplines) to capture the applicability dimension and paradigmatic development dimension respectively.

Correlation analysis was conducted using the chi-square test in Stata 16 to examine the relationships between academic discipline characteristics and GenAI-related engagement (Fig. 2). This 3 × 3 analysis was designed to illustrate how various disciplinary attributes influence AI knowledge, usage intention, and engagement with AI tools for different tasks. Specifically, we analyzed the associations between three sets of

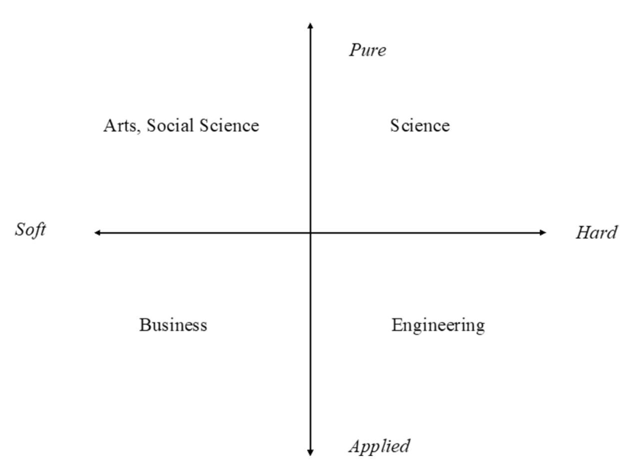

Fig. 1 Categorization of academic disciplines

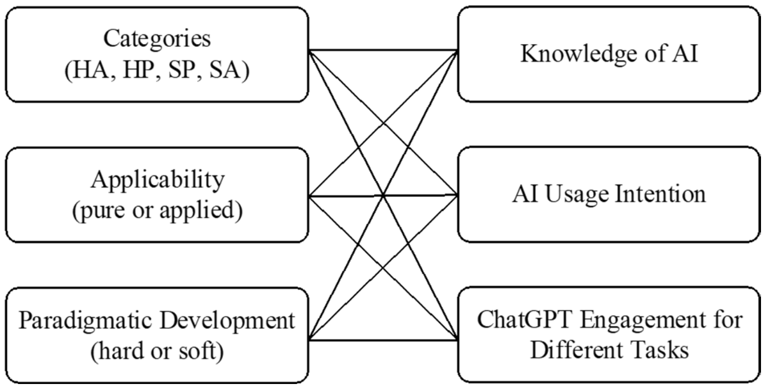

Fig. 2 Correlation analysis of academic discipline characteristics and GenAI-related engagement

Table 2 Descriptive of statistics

Variable	Obs	Mean	Std.dev	Min	Max
Category	193	2.135	1.081	1	4
soft_hard	193	0.477	0.501	0	1
pure_applied	193	0.523	0.501	0	1
KnowAI_dummy	193	0.943	0.232	0	1
UseAI_ordered	193	2.653	0.713	1	3
Routine_task	193	0.653	0.477	0	1
Cognitive_task	193	0.793	0.406	0	1

variables: (1) Academic discipline categories: Hard-Applied (HA), Hard-Pure (HP), Soft-Pure (SP), and Soft-Applied (SA); (2) Biglan's dimensions: Applicability (pure or applied) and Paradigmatic Development (hard or soft); and (3) GenAI engagement indicators: AI knowledge, AI usage patterns, and task-specific AI use (cognitive and routine).

Results

The sample is nearly evenly distributed between disciplinary categories. For the soft vs. hard distinction, 52% of the sample is classified as soft disciplines and 48% as hard disciplines. Similarly, for the pure vs. applied distinction, 52% are classified as applied disciplines and 48% as pure disciplines.

Responses from students indicate high AI awareness among respondents, with 94.3% possessing knowledge of AI (Table 2). This widespread familiarity suggests that AI has become a prominent topic across various academic disciplines. AI usage frequency is also substantial, with 79.27% of students already using AI, 6.74% not yet using but intending to, and 13.99% of respondents not planning to use AI. This indicates that a significant majority of students are actively incorporating AI into their academic activities.

Regarding task-specific AI use, 65% of respondents employ AI for routine tasks, while a higher proportion of 79% utilize AI for cognitive tasks. This preference for leveraging AI in complex, thought-intensive activities rather than simple, repetitive tasks suggests that students value AI more for its ability to assist with higher-order thinking processes.

Table 3 Correlation table using chi-square statistics

Variable	Categories (1 = Hard and Applied; 2 = Soft and Pure; 3 = Hard and Pure; 4 = Soft and Applied)	Pure/Applied Fields (0 = Pure; 1 = Applied)	Soft/Hard Fields (0 = Soft; 1 = Hard)
Knowledge of AI	9.363**	8.743***	1.945
AI Usage Intention	21.680***	7.978**	6.057**
ChatGPT engagement (Cognitive)	8.140**	7.955***	0.540
ChatGPT engagement (Routine)	6.367*	4.571**	0.103

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

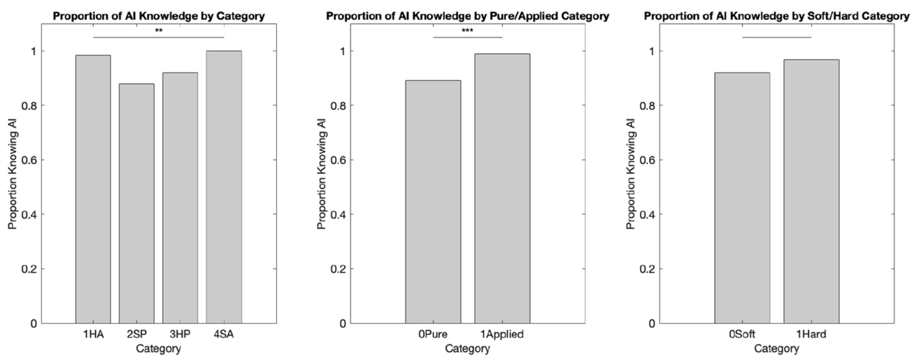

Fig. 3 AI knowledge

These statistics highlight high AI awareness and usage among undergraduate students, with a notable preference for AI in cognitive tasks over routine tasks.

The correlation analysis reveals significant relationships between academic discipline characteristics and various dimensions of AI engagement (Table 3). We found that the nature of academic fields (pure vs. applied) significantly influences students' AI knowledge and usage intentions, with applied fields consistently demonstrating higher levels of engagement compared to pure fields. Additionally, while the use of AI for routine tasks is relatively uniform across disciplines, there are significant differences in AI engagement for cognitive tasks, with applied fields exhibiting higher involvement.

AI knowledge

The findings of the chi-square test ($\chi^2 = 9.363$, $p = 0.025$) suggest that there are considerable variations in knowledge of AI among different groups. Individuals grouped in the HA (Hard-Applied) and SA (Soft-Applied) categories have higher levels of AI knowledge, but those in the SP (Soft-Pure) category exhibit a comparatively lower level (Fig. 3, left). This statistically significant disparity implies that the classification of disciplines (hard/soft, applied/pure) is associated with AI knowledge levels.

There was a strong correlation between the type of field (pure vs. applied) and knowledge of AI ($\chi^2 = 8.743$, $p = 0.003$). Specifically, individuals in applied fields are more likely to have knowledge of AI compared to those in pure fields (Fig. 3, middle), suggesting that the applicability of the academic field plays a role in AI knowledge acquisition or exposure.

The analysis of the relationship between the type of field (soft vs. hard) and knowledge of AI yielded no significant association ($\chi^2 = 1.945$, $p = 0.163$). This lack of statistical significance suggests that the paradigmatic distinction between soft and hard fields does not substantially influence the likelihood of individuals having AI knowledge (Fig. 3, right).

These results collectively indicate that while the pure/applied nature of academic fields is associated with differences in AI knowledge, the soft/hard distinction does not show a significant relationship.

AI usage

Analysis reveals a significant correlation between academic categories and AI usage intention ($\chi^2 = 21.680$, $p = 0.001$). Applied fields, both hard and soft, demonstrate a higher tendency for AI adoption, presumably due to their practical and solution-oriented focus (Fig. 4, left). In contrast, pure fields—particularly soft pure disciplines—display a noticeable reluctance towards AI integration. This hesitancy may be attributed to their predominantly theoretical focus and limited emphasis on technological applications.

The pure/applied dichotomy significantly influences AI usage intention ($\chi^2 = 7.978$, $p = 0.019$). Applied disciplines have a higher rate of current AI adoption (Fig. 4, middle). In contrast, Pure fields display a more varied distribution, including both potential future adopters and those reluctant to use AI. This pattern suggests that the applied nature of a field may catalyze earlier AI integration.

The soft/hard dimension also plays a crucial role in shaping AI usage intentions ($\chi^2 = 6.057$, $p = 0.048$). Hard fields exhibit a stronger inclination towards future AI adoption among current non-users, while soft fields show a higher proportion of individuals with no intention to incorporate AI (Fig. 4, right). This distinction highlights the varying receptivity to AI across different academic domains.

In summary, these findings underscore the complex interplay between disciplinary characteristics and AI adoption in academia. Both the soft/hard and pure/applied distinctions significantly vary in terms of AI usage intentions. This nuanced understanding suggests that strategies for promoting AI integration in higher education may require tailored approaches, considering the unique attributes and needs of each academic field.

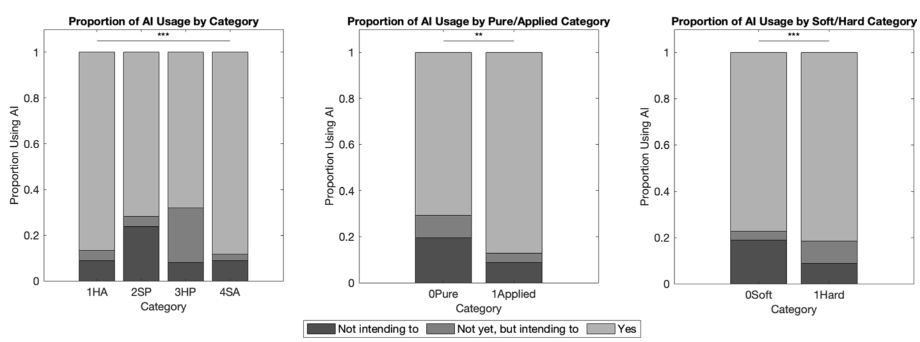

Fig. 4 AI usage

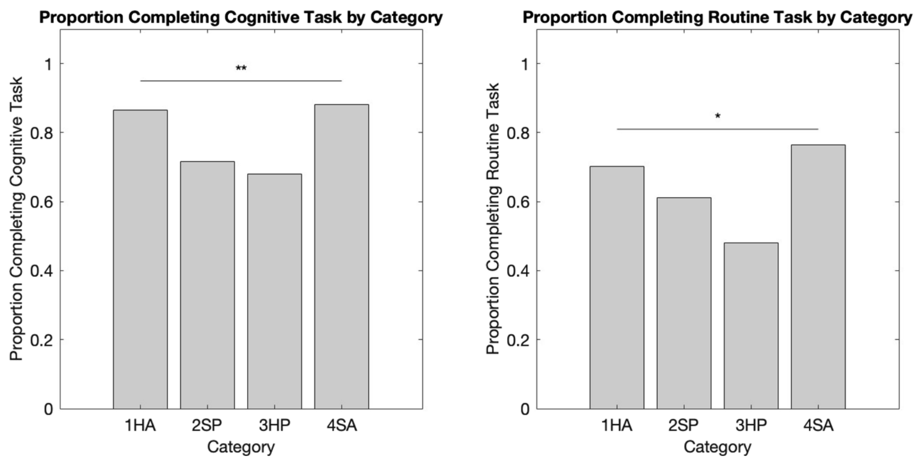

Fig. 5 Categories and ChatGPT engagement for different tasks

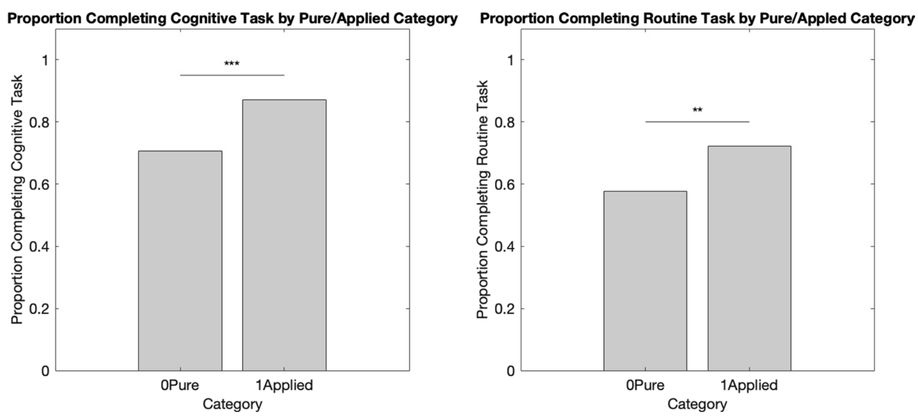

Fig. 6 Pure/applied fields and ChatGPT engagement for different tasks

AI tasks

Analysis reveals no significant difference in routine task engagement across categories ($\chi^2=6.367$, $p=0.095$). However, cognitive task engagement varies significantly among categories ($\chi^2=8.140$, $p=0.043$). As shown in Fig. 5, the HA and SA categories lead in cognitive task engagement, whereas the SP and HP disciplines show lower levels of engagement. This disparity likely stems from the prevalence of higher-order thinking and problem-solving requirements in certain fields. Notably, applied disciplines (both hard and soft) exhibit greater AI utilization for complex, cognitive activities, aligning with their practical, solution-oriented focus.

The pure/applied distinction significantly influences ChatGPT engagement (Fig. 6). For cognitive tasks, a notable association emerges ($\chi^2=7.955$, $p=0.005$), with applied fields showing higher engagement. Similarly, routine task engagement displays a significant correlation ($\chi^2=4.571$, $p=0.033$), indicating that applied fields are more likely to leverage ChatGPT for both routine and cognitive tasks compared to pure fields.

Interestingly, the soft/hard classification (Fig. 7) shows no significant association with ChatGPT engagement for either routine ($\chi^2=0.103$, $p=0.748$) or cognitive tasks

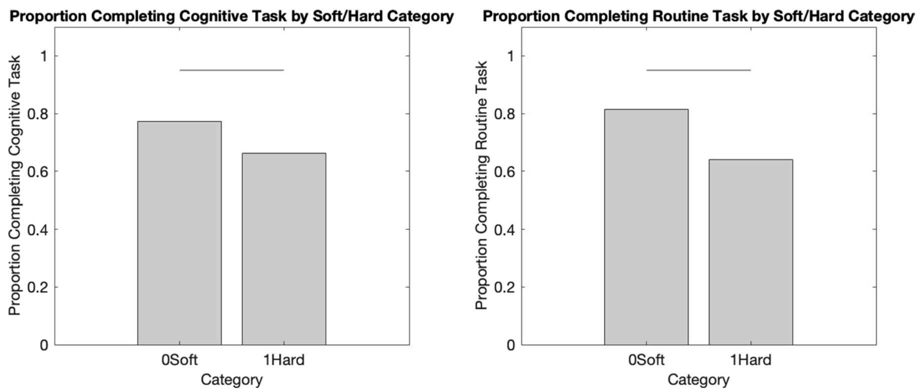

Fig. 7 Soft/Hard Fields and ChatGPT Engagement for Different Tasks

($\chi^2 = 0.540$, $p = 0.462$). This suggests that the soft/hard distinction does not substantially influence AI tool usage patterns for academic tasks.

In summary, these findings highlight that while the pure/applied dimension significantly shapes ChatGPT engagement patterns—with applied fields demonstrating higher engagement across both routine and cognitive tasks—the soft/hard distinction appears to have minimal impact.

Discussion

This study investigates the influence of academic discipline characteristics on undergraduate students' engagement with GenAI, considering knowledge, usage, and task types. Hypotheses 1 and 2 are supported, as students' AI usage patterns and AI knowledge differ significantly across academic disciplines. Applied fields, both hard and soft, consistently demonstrate higher AI knowledge and usage intentions. The pure/applied distinction is significant, with applied fields showing greater AI knowledge, current adoption, and usage intention. While the soft/hard distinction is less influential overall, it does impact usage intention, with hard fields showing greater future intention to use AI. Regarding AI task engagement, categories show significant differences in cognitive task engagement(H3), but not in routine tasks (H4). The pure/applied distinction is significant for both routine and cognitive tasks, with applied fields showing higher engagement across both types. Notably, the soft/hard distinction has no significant impact on task engagement. Overall, the applied nature of a discipline consistently correlates with higher AI engagement across all dimensions examined. In contrast, the hard/soft distinction has a more limited influence, primarily affecting usage intentions. These results suggest that the practical orientation of applied fields may be a key driver in AI adoption and utilization in academic settings. These findings contribute to the existing literature on disciplinary differences and task-based automation in technology adoption by identifying the contextual factors that influence AI engagement in higher education.

Our first finding shows the role of applicability in driving AI adoption and understanding among undergraduate students. This finding aligns with previous research by Gray (2024), who found greater AI integration in engineering and natural sciences, and Raman et al. (2024), who found that information and computing sciences, and biomedical and clinical sciences, were the disciplines most engaged with ChatGPT. We propose that these variations in technology adoption can be attributed to differences in paradigmatic structures and practical applications across disciplines, as highlighted by Biglan (1973). In particular, applied fields inherently emphasize practical utility and tangible outcomes (Venkatesh et al., 2003). As a result, students in these fields may be more aware of the potential benefits AI technologies can provide, such as increased efficiency, new research possibilities, or enhanced real-world results. This clear understanding of AI's utility could inspire a stronger drive to learn about and utilize AI, even if it requires modifying existing methods and approaches. Furthermore, given the potential for commercial or societal applications of their work (Becher, 1994; Etzkowitz et al., 2000), applied fields may have greater access to funding and resources for AI-related projects and implementation. This external support could create a positive feedback loop, enabling applied fields to advance more rapidly in AI adoption and development compared to theoretical fields.

The implications of this finding apply to both applied and pure sciences. While the application-driven approach to AI in undergraduate education for applied fields offers clear benefits, an excessive focus on practical implementation may lead to neglecting the fundamental, long-term knowledge essential for driving paradigmatic shifts and unlocking new possibilities in AI. Theoretical and foundational learning plays an essential role in expanding the boundaries of what is feasible and establishing the groundwork for future breakthroughs. Therefore, it is critical to strike a balance between promoting AI adoption in applied fields and fostering theoretical foundations. Conversely, the lower AI engagement observed in pure sciences raises concerns about potential missed opportunities for groundbreaking discoveries and methodological advancements. This engagement gap could hinder pure sciences' contributions to interdisciplinary collaborations involving AI, potentially slowing fundamental scientific progress. The dichotomy between applied and pure sciences in AI adoption presents a challenge that requires careful consideration and targeted interventions.

Moreover, our study reveals that students across disciplines have similar levels of engagement with AI for routine tasks but differ in cognitive task engagement, suggesting that the nature of the task plays a significant role in shaping students' willingness to engage with AI. This finding aligns with Andersen et al. (2024), who found that researchers regarded using GenAI for tasks like language editing and data analysis as acceptable, while its application in fundamental tasks such as designing experiments and peer review raised ethical concerns. Our findings further highlight how these task differences intersect with disciplinary contexts. We argue that the distinction in task-level engagement might stem from the different underlying epistemological and methodological approaches of each field. Technical disciplines tend to integrate AI into complex problem-solving processes, while humanities and social sciences use AI as a supplementary tool. As the levels of complexity and domain-specific knowledge required for cognitive tasks vary in different disciplinary contexts (Meyer, 2003), students in fields where cognitive tasks are more intricate may hesitate to rely on AI tools, feeling that AI cannot fully grasp the necessary nuances and context-specific knowledge.

Additionally, the perceived value and appropriateness of using AI for cognitive tasks vary across disciplines. In fields such as creative writing or art, AI may be seen as inauthentic or unethical, while in fields like computer science or engineering, AI may be viewed as a valuable tool for enhancing cognitive tasks. The implications of this finding align with concerns raised by Tlili et al. (2023), who identified ethical issues related to AI, such as its potential to encourage plagiarism, breed laziness among users, and provide biased or fake information.

Our research suggests that engineering students may be more likely to use AI for cognitive tasks compared to their peers in other disciplines. While AI tools can enhance problem-solving capabilities and increase efficiency, an over-reliance on these tools could potentially impede the development of critical thinking, independent problem-solving, and domain-specific expertise. To address these concerns, educators must carefully integrate AI into their curricula in a way that nurtures cognitive development. For example, instructors could have students use AI to generate initial solutions, followed by critical evaluation, refinement, and justification through their own analysis and domain knowledge. This approach allows students to benefit from AI while actively engaging in cognitive processes necessary for skill development. The key challenge lies in leveraging AI's capabilities while ensuring the development of essential field-specific cognitive skills. Therefore, curricula should position AI as a complement to, rather than a substitute for, students' critical thinking and problem-solving efforts.

Contributions and limitations

Our study offers both theoretical and practical contributions to the understanding of GenAI engagement in higher education. Theoretically, we advance the knowledge of disciplinary differences in GenAI engagement by bridging two previously disconnected areas of research: the framework of disciplinary cultures and the concept of task-based automation. While prior studies have examined these concepts independently, our research is the first to integrate them, offering a new perspective through which to analyse the contextual factors shaping AI engagement in higher education.

Practically, our findings have significant implications for curriculum design and institutional AI policies. By showing that applied fields exhibit higher AI engagement and usage, our study suggests that AI-related curricula should leverage the strengths of these fields while promoting balanced development in pure sciences. Additionally, the findings highlight the need to integrate AI into cognitive tasks in a way that fosters critical thinking and independent problem-solving. Educators should design AI-enhanced learning activities that encourage students to critically engage with AI-generated solutions, ensuring that AI complements rather than replaces essential cognitive skills. These practical insights can help universities implement AI technologies that enhance learning outcomes while addressing discipline-specific needs.

Some limitations to our study should be acknowledged. Firstly, our study relies on a cross-sectional design, which captures data at a single point in time. This design limits our ability to establish causal relationships between academic disciplines and GenAI engagement, as we can only observe correlations rather than how these factors evolve or influence each other over time. The lack of temporal data prevents us from determining whether observed patterns in AI usage and knowledge are enduring or subject to change due to emerging technologies or shifting academic practices. Future research could address this limitation by adopting longitudinal designs to track changes in AI usage and engagement over time.

Second, our study relies on data from a single university in Singapore, which may limit the generalizability of the findings to other global educational contexts. This focus on one geographic location may overlook variations in AI engagement that could exist in different educational and cultural settings. However, we argue that this limitation does not significantly undermine our core contributions, as Becher (1994) suggests that disciplinary cultures share norms and practices that transcend institutional and national boundaries, reinforced by academic mobility, shared literature, and international collaboration. To address this limitation, future research could conduct comparative studies across multiple institutions and regions to confirm the applicability of our findings in different educational systems. Such studies could also explore how regional, institutional, and cultural factors influence AI engagement, further enhancing the practical relevance of our findings for higher education globally.

Lastly, our study focuses on undergraduate students, but future research could also investigate the perspectives and practices of faculty members across different disciplines. Examining how educators perceive and integrate GenAI tools into their teaching and research activities could provide valuable insights into the institutional and pedagogical factors influencing student engagement with these technologies. For example, exploring how faculty members incorporate GenAI into curricula, assessment practices, and research projects could shed light on how disciplinary norms and values shape the adoption and use of these tools. Additionally, understanding faculty attitudes towards GenAI, including their perceived benefits, challenges, and ethical considerations, could inform the development of institutional policies and support structures that promote GenAI's responsible and effective integration in higher education.

Conclusion

In conclusion, our findings challenge the notion of a homogenous "digital native" generation and indicate disciplinary differences in how students interact with AI with the consideration of task differentiation. Applied domains demonstrated higher levels of AI knowledge and intention to use AI than pure domains, emphasising the importance of practicality in driving AI adoption. This suggests the need for educators and policymakers to effectively communicate the tangible benefits of AI within the context of each discipline, fostering a clearer understanding of its potential applications and encouraging broader engagement. Significant differences in AI engagement for cognitive tasks across disciplines also underscore the need for targeted AI integration strategies. Educators must develop AI-infused curricula that align with each discipline's unique traditions, ensuring AI enhances rather than replaces critical thinking and creativity. As AI continues to reshape higher education, our study highlights the importance of adapting to this new reality in a manner that is informed by a deep understanding of the disciplinary contexts in which AI is deployed.

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Author contributions

Yao QU: methodology, Writing—original draft, Writing—review & editing; Michelle TAN: data curation; Jue WANG: supervision, Writing—review & editing, Funding acquisition. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated during this study are not publicly available due to privacy and ethical restrictions. Aggregated data may be available from the corresponding author upon reasonable request, subject to institutional approval.

Declarations

Competing interests
The authors declare that they have no competing interests.

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