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MAPPING GENAI LITERACY: DISCIPLINARY DIFFERENCES, LATENT PROFILES, AND PERCEPTIONS AMONG EMI UNDERGRADUATES

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ABSTRACT

Aim/Purpose	This study aims to explore the Generative AI (GenAI) literacy of English-medium instruction (EMI) undergraduates, with a particular focus on disciplinary variations across engineering, mathematics, and humanities and social sciences. Specifically, it seeks to a) examine differences in GenAI literacy across disciplines, b) identify distinct literacy profiles among disciplinary groups, and c) understand students' self-perceptions of their GenAI literacy.
Background	The advent of GenAI tools has reshaped higher education, offering personalised academic support and aiding non-native English speakers. While traditionally focused on STEM fields, the widespread adoption of GenAI, alongside concerns about accuracy and ethics, emphasises the urgent need for GenAI literacy education across all disciplines. However, gaps remain in the literature regarding how students' GenAI literacy varies across disciplines and how their underlying literacy profiles are shaped, particularly in EMI contexts, where non-native English-speaking students face additional linguistic challenges.
Methodology	Utilising a mixed-methods approach, the research assesses five critical dimensions of GenAI literacy: basic technical proficiency, communication proficiency, creative application, critical evaluation, and ethical competence. The quantitative

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phase, which included 347 questionnaire participants recruited via convenience sampling, employed the Kruskal-Wallis test to examine disciplinary differences in GenAI competencies. Further, a multigroup latent profile analysis was conducted to identify distinct literacy profiles. To complement the quantitative findings, follow-up semi-structured interviews were carried out with 24 students to collect in-depth qualitative data. These interviewees were drawn from the questionnaire participants using a nested sampling strategy. Reflexive thematic analysis was then applied to uncover key themes related to students' perceived GenAI literacy.

Contribution This study highlights notable variations in GenAI literacy among students across different disciplines and identifies distinct learner profiles within an EMI university context. The findings underscore the importance of considering both disciplinary and learner-profile factors when developing educational strategies. This work offers a foundation for designing equitable and targeted strategies to develop students' AI literacy across all disciplines, a pressing need in EMI contexts where learners navigate additional linguistic challenges.

Findings The Kruskal-Wallis test results indicated that, with the exception of ethical competence, engineering students outperformed their peers in mathematics, humanities, and social sciences across four dimensions of GenAI literacy: basic technical proficiency, communication proficiency, creative application, and critical evaluation. Additionally, the multigroup latent profile analysis identified three distinct literacy profiles across disciplines: Foundational Learners, Balanced Practitioners, and Proficient Achievers. Complementary qualitative insights from interviews corroborated these findings and provided nuanced explanations of the underlying patterns.

Recommendations for Practitioners Synthesising these insights, evidence-based pedagogical recommendations are proposed: the integration of AI literacy courses across all disciplines to foster foundational competencies and equitable access, and the implementation of profile-specific educational strategies to enhance personalised learning.

Recommendations for Researchers Refining methods for assessing GenAI literacy is recommended for future studies to enhance their validity and reliability. This includes employing more representative sampling, integrating observation-based or task-based measures alongside self-reported literacy levels, and further refining the theoretical frameworks underpinning AI literacy in response to evolving technologies.

Impact on Society The insights from this study into GenAI literacy and its disciplinary variations will enable universities to develop more responsive and inclusive educational strategies, ultimately fostering a more AI-literate society. This will ensure that graduates across all disciplines are better prepared to effectively and critically engage with AI technologies in their future careers and daily lives.

Future Research Future research should consider stratified sampling across multiple institutions, regions, and cross-national contexts to capture a more representative picture of GenAI engagement and facilitate meaningful comparisons across educational systems. In addition, while the study focused on undergraduates, postgraduate students, and academic staff are also critical stakeholders in the AI literacy agenda. Investigating how these groups engage with GenAI could provide valuable comparative insights. More importantly, the identification of learner profiles also raises new questions about movement between profiles over time and the kinds of interventions that support such transitions. Longitudinal studies and action research involving instructional design experiments could help clarify

	how GenAI literacy evolves and what pedagogical strategies are most effective for supporting growth.

Keywords	GenAI literacy, higher education, interdisciplinary AI education, educational equity, learner profiles

INTRODUCTION

The advent of large language models, such as OpenAI's ChatGPT, in November 2022 has sparked a transformative shift in higher education, altering how students learn and interact with digital content. These models, part of a broader category known as Generative AI (GenAI), are renowned for their ability to produce novel and varied outputs, significantly impacting student learning by providing personalised, on-demand academic support (Peres et al., 2023; Tzirides et al., 2024). However, the dependence on GenAI raises substantial concerns regarding the accuracy of its outputs and the potential for fostering an over-reliance that could diminish critical thinking and problem-solving skills among students (Chan & Tsi, 2023; Harrer, 2023).

Ethical considerations, particularly those related to privacy and academic integrity, are also pressing, alongside concerns that GenAI may alter job markets and impact future employment opportunities (Ghotbi et al., 2022; Gillissen et al., 2022). As the landscape of higher education evolves with these technologies, the imperative grows for institutions to equip students not only with the knowledge to use these tools responsibly but also with the skills to innovate and adapt in a rapidly changing world (Abdelwahab et al., 2023; King, 2017; Pelletier et al., 2023). In response, researchers have called for the development of integrated curricula that embed AI concepts across disciplines, enabling students to build foundational knowledge and apply AI tools critically and ethically (Beckman et al., 2025; Chiu, 2024; Krakowski et al., 2022).

While these efforts highlight a growing consensus on the importance of inclusive AI education, gaps remain in understanding how disciplinary cultures shape students' GenAI literacy. Empirical research reveals clear disciplinary differences in AI adoption, with technology-oriented fields such as computer science and engineering engaging more actively than the arts, humanities, and social sciences (Qu et al., 2024; Raman et al., 2024). To date, most AI-related education has been concentrated in disciplines such as computer science and engineering (Cantú-Ortiz et al., 2020; Kandlhofer et al., 2016), where students report finding GenAI tools invaluable for consolidating knowledge and supporting complex problem-solving (Valeri et al., 2025).

In contrast, the GenAI literacy needs of students in other disciplines remain underexplored. Existing evidence underscores the influence of disciplinary background on AI engagement, pointing to the need for a more nuanced understanding of how such differences shape students' GenAI literacy, given the multifaceted nature of this construct. Furthermore, these issues are particularly under-researched in English-medium instruction (EMI) contexts, where non-native English-speaking students navigate unique linguistic complexities (Rose et al., 2020). Addressing these gaps is critical for developing inclusive GenAI literacy initiatives that respond to diverse learning needs.

This study explores the GenAI literacy of English-medium instruction (EMI) undergraduates, with a particular focus on disciplinary variations. Specifically, it aims to (a) examine differences in GenAI literacy across disciplines, (b) identify distinct literacy profiles among disciplinary groups, and (c) understand students' self-perceptions of their GenAI literacy. By aligning these objectives with the gaps identified above, the study seeks to advance understanding of how disciplinary contexts shape EMI students' GenAI literacy.

LITERATURE REVIEW

DEFINING AI LITERACY IN THE AGE OF GENAI

As the integration of AI across various academic disciplines gains momentum, the concept of AI literacy, first introduced by Konishi (2015), has become a cornerstone in educational strategies. Though the importance of AI literacy is widely acknowledged, consensus on its definition remains elusive, reflecting the field's nascent stage and the evolving nature of AI technologies (Biagini et al., 2024; Laupichler et al., 2022). Historically, AI literacy focused on the ability to comprehend fundamental AI technologies and their applications (Kandlhofer et al., 2019). However, the advent of GenAI models has expanded this scope significantly. Long and Magerko (2020) provided a foundational definition, describing AI literacy as a set of competencies for critically evaluating AI technologies, communicating and collaborating effectively with AI, and utilising AI tools in various settings. This framework highlights critical evaluation, communication proficiency, and practical application as pivotal dimensions, which have gained prominence with the rise of GenAI (Ding et al., 2023; Kelly et al., 2023; Ngo & Hastie, 2025; Walter, 2024).

Further developments in the discourse have introduced additional competencies, such as technical proficiency and ethical awareness, which are essential for navigating the complexities of the GenAI landscape. Ng et al. (2021) conducted a systematic review of 30 AI literacy studies, proposing a hierarchy of competencies arranged by cognitive complexity, ranging from a basic understanding to the practical use, critical evaluation, and design of AI applications, as well as the ethical use of AI. While this model is comprehensive, it is worth noting that the design of AI applications is predominantly suited for those with a technical background, thus limiting its relevance for non-experts. Although advanced technical knowledge is important for developing AI literacy, Long and Magerko (2020) argued that it is not a necessary prerequisite for non-AI experts. Extending this line of work, Cuomo et al. (2022) proposed a more inclusive framework appropriate for non-specialist users, emphasising knowledge of AI fundamentals, operational abilities, critical evaluation, and ethical considerations.

Recent studies underscore the synergistic outcomes of human-AI collaboration, often surpassing what either can achieve independently (Fügener et al., 2021). Reflecting this shift towards more dynamic interaction with AI, there has been a growing recognition of creativity as a vital component of AI literacy. While earlier frameworks have emphasised the practical application of AI, this study adopts a different approach by focusing on the creative application of AI. This dimension foregrounds how GenAI can be used to generate novel ideas and co-create content, extending beyond functional use into the realm of innovation (Lee & Park, 2024; Ng et al., 2022; Reddy et al., 2020). By reconceptualising "practical use" as "creative application," this study better captures the affordances of GenAI in educational contexts, particularly its potential to foster innovation and deeper intellectual engagement. Moreover, this shift aligns with broader educational goals of equipping students not only to consume AI outputs passively but to become active and creative participants in an AI-mediated academic landscape (Chiu, 2024). This reconceptualisation informs the study's approach to assessing and developing GenAI literacy across disciplines.

Drawing on previous theoretical frameworks and tailoring them to the context of higher education, particularly for students without specialised training in AI, this study examines five key dimensions of EMI undergraduates' GenAI literacy:

1. *Basic technical proficiency:* The basic technical abilities needed to understand and use GenAI tools (Cuomo et al., 2022).
2. *Communication proficiency:* The ability to communicate effectively with GenAI tools (Ding et al., 2023; Lee & Park, 2024; Long & Magerko, 2020; Walter, 2024).
3. *Creative application:* The ability to use GenAI tools to generate new ideas or solutions to enhance creativity and innovation (Lee & Park, 2024; Reddy et al., 2020).

4. *Critical evaluation:* The ability to evaluate and analyse the accuracy, reliability, errors, completeness, and bias of GenAI tools' responses (Cuomo et al., 2022; Lee & Park, 2024; Long & Magerko, 2020; Ng et al., 2021).
5. *Ethical competence:* The ability to identify ethical or legal issues and use GenAI tools in an ethical way (Cuomo et al., 2022; Lee & Park, 2024; Ng et al., 2021).

Table 1 summarises the similarities and differences between existing AI literacy models and the current study's framework.

Table 1. Key dimensions of AI literacy across selected models

Dimension	Long and Magerko (2020)	Ng et al. (2021)	Cuomo et al. (2022)	This study (adapted from Lee & Park, 2024)
Basic Technical Proficiency	✕ (not included)	✕ (involves high-level technical competencies, e.g., developing AI applications)	✓	✓ (involves basic technical competencies of using GenAI, suitable for non-specialists)
Communication Proficiency	✓	✕ (not explicitly mentioned)	✕ (not explicitly mentioned)	✓
Creative Application	✕ (focuses on the practical utility of GenAI in real-world contexts)	✕ (focuses on the practical utility of GenAI in real-world contexts)	✕ (focuses on the practical utility of GenAI in real-world contexts)	✓ (focuses on innovative and novel application of GenAI)
Critical Evaluation	✓	✓	✓	✓
Ethical Competence	✕ (focuses on specialists' ethical considerations in the design and development of AI technologies)	✓	✓	✓

By structuring GenAI literacy around these five dimensions, this study provides a comprehensive yet practical framework for understanding EMI undergraduates' GenAI competencies. This approach emphasises the multidimensional nature of AI literacy by extending beyond technical knowledge to include communicative, creative, critical, and ethical considerations.

Developing GenAI Literacy Among University Students

Research into GenAI literacy among university students has underscored the significance of the five core dimensions, which include basic technical proficiency, communication proficiency, creative application, critical evaluation, and ethical competence. Studies by Laupichler et al. (2023) and Wang et al. (2023) identify basic technical proficiency as a fundamental component of digital literacy yet reveal a pervasive gap in students' understanding of AI technologies like machine learning and large language models (Biagini et al., 2024; Valeri et al., 2025). This understanding is crucial not only for utilising AI (Chan & Hu, 2023) but also for enhancing interaction strategies such as effective prompting (Knoth et al., 2024).

In terms of communication proficiency, the ability to craft effective prompts for GenAI emerges as a vital skill. This skill not only affects user experience but also shapes perceptions regarding the utility of GenAI (Tassoti, 2024; Theophilou et al., 2023). However, despite their capabilities, many students struggle with formulating well-defined prompts, which results in inaccurate or overly generalised outputs (Kelly et al., 2023). Analyses of students' interactions with GenAI indicate that they frequently rely on an iterative, trial-and-error process, making multiple adjustments before obtaining satisfactory results (Oppenlaender, 2023; Tzirides et al., 2024).

In parallel, the creative application of GenAI presents a dual-edged sword. While there is potential for these tools to foster innovation by generating new ideas and enhancing co-creation (Benbya et al., 2024; Fügener et al., 2021; Ng et al., 2021), reliance on AI-generated content could potentially stifle creativity over time (Chan & Hu, 2023; Chan & Tsi, 2023). Nevertheless, experiential learning approaches, such as applying AI tools to real-world problem-solving, have been found to foster creativity and critical thinking (Southworth et al., 2023), both of which are essential skills for successful human-AI collaboration (Lee & Park, 2024).

Equally important is the development of critical evaluation skills. Although many students exhibit limited trust in GenAI outputs due to issues like inaccuracies or lack of references (Valeri et al., 2025), those with more substantial disciplinary knowledge tend to critically engage and refine AI outputs more effectively (Chiu, 2024). This suggests a need for foundational domain knowledge before integrating GenAI into educational settings, with further calls for structured educational activities to enhance these evaluation skills (Ngo & Hastie, 2025; Walter, 2024). At the same time, another line of research (e.g., Kelly et al., 2023; Ma, 2024) suggests that excessive scepticism and distrust towards GenAI may result in reduced engagement and lower adoption rates, emphasising the critical role of trust in AI adoption.

Finally, ethical competence remains a critical yet under-supported dimension. Many higher education institutions lack clear policies on GenAI use, leaving individual instructors to make independent decisions on its implementation (McMurtrie, 2023). Attewell (2025) further reported that students often perceived a lack of institutional support and guidelines for responsible GenAI usage. With growing awareness of the ethical implications of GenAI use, there is an urgent call for clear institutional policies and educational guidelines to ensure the responsible use of AI technologies (Borenstein & Howard, 2021; Wong et al., 2020).

Taken together, this comprehensive analysis highlights the complex and multifaceted nature of GenAI literacy, emphasising the need for a more nuanced understanding, particularly regarding how student competencies vary across disciplines and what distinct AI literacy learner profiles exist. Understanding these differences can enable educators to provide tailored and targeted support that meets diverse student needs.

Disciplinary Variations in University Students' GenAI Literacy

Disciplinary background has been shown to influence students' familiarity with and engagement in digital and AI-related tools. As Ng et al. (2023) noted, AI literacy programs were predominantly designed for and accessed by students in computer science, with few initiatives reaching beyond this cohort. As a result, these engineering students often received structured exposure to computational thinking, programming, and AI-focused tasks (Ng et al., 2023), which could enhance their readiness to use GenAI tools. This observation is corroborated by Qu et al. (2024), who found that students in applied and technology-oriented disciplines, such as engineering, demonstrated higher levels of GenAI knowledge, stronger intentions to use GenAI, and greater engagement in cognitive tasks than students in pure disciplines, including humanities, arts, and social sciences. Raman et al. (2024) further explained that such disciplinary differences might stem from a greater perceived ease of use and educational relevance in technology-aligned fields, such as computing and biomedical sciences, while lower engagement in the arts and social sciences was shaped more by ethical concerns regarding the use of GenAI tools.

Within STEM disciplines, engagement with GenAI can vary depending on the nature of the discipline. For example, Valeri et al. (2025) reported that students in biology and chemistry utilised GenAI more than those in mathematics and physics, likely due to the historical limitations of language models in performing accurate calculations (Polverini & Gregorcic, 2024). This suggests that while GenAI tools are evolving, their application in quantitatively intensive disciplines remains challenging, indicating a possible divergence in AI competencies even within STEM fields.

These findings indicate that a disciplinary background, supported by curricular exposure, technical skills, and the domain-specific applicability of AI tools, emerges as a meaningful factor in understanding variations in university students' GenAI literacy. While existing studies have made advancements in understanding how different disciplines interact with GenAI, a comprehensive understanding of the multidimensional nature of students' GenAI literacy and their learner profiles across disciplines is still lacking. Drawing on prior findings, this study examines differences in GenAI literacy within STEM disciplines (engineering and mathematics) and between STEM and non-STEM fields, with the humanities and social sciences representing the non-STEM group.

Despite the growing body of knowledge, literature on these issues remains particularly limited within the context of EMI universities. In such institutions, where subject knowledge is delivered in English to non-native English-speaking students in their home countries, learners often face challenges in navigating linguistically complex academic environments (Alqarni et al., 2024; Uçar & Soruç, 2018). The rapid integration of GenAI tools has shown promise in supporting these students by helping them overcome language barriers and enhance academic engagement (Chan & Lee, 2023; Meyer et al., 2023). As Hong (2022) observed, the ability to leverage advanced chatbot technologies could help mediate the linguistic difficulties faced by EMI students. While earlier studies identified English proficiency as a key factor influencing EMI learners' academic performance (Rose et al., 2020; Xie & Curle, 2022) and their ability to seek academic information in English (Harvey & Brazier, 2022), a more recent study by Mai and Van Hanh (2024) reported that English proficiency did not significantly influence EMI students' use of GenAI tools to seek explanations, generate ideas, and co-create content. This finding highlights the potential of GenAI tools to facilitate content knowledge acquisition for EMI learners, regardless of language proficiency. The present study aims to extend this work by examining how EMI students across disciplines vary in their competencies in using GenAI tools.

METHODOLOGY

This study employed a mixed-methods approach to integrate quantitative and qualitative findings, providing a comprehensive understanding of the research problem (Creswell & Plano Clark, 2018). To address the research gaps, it explores Chinese EMI undergraduates' GenAI literacy by answering the following research questions (RQs):

- **RQ1**: Is there a significant difference in EMI undergraduates' GenAI literacy by discipline (i.e., engineering, mathematics, and humanities and social sciences)?
- **RQ2**: What latent profiles of GenAI literacy can be identified among EMI undergraduates across disciplines?
- **RQ3**: How do EMI undergraduates from different disciplines perceive their GenAI literacy?

STUDY CONTEXT AND PARTICIPANT RECRUITMENT

This research was conducted at a private transnational EMI university in eastern China from June to December 2024. As a pioneer in Sino-foreign higher education collaborations, this university offers a range of EMI programs in disciplines such as science, engineering, mathematics, humanities and social sciences, business, and artificial intelligence. English functions as the official working language, used in teaching, learning, assessments, and administration, accounting for over 90% of language use on campus. Each year, approximately 4,000–5,000 Chinese students, primarily from the first tier of the national college entrance examination and typically scoring over 110 out of 150 on its English component, are admitted into the university and begin a preparatory Year 1 programme that includes courses such as English for Academic Purposes and Mathematics. The faculty body is internationally diverse, with staff recruited from countries such as the U.S., the U.K., Canada, Australia, France, and Singapore, while many local Chinese faculty members also hold overseas educational qualifications. This distinctive context, with its Year 1 preparatory programme and mature EMI curricula, offers valuable insights into EMI practices, though it may limit the generalisability of the findings to other EMI contexts. To support the integration of GenAI in education, the university launched its own GenAI platform, "XIPU AI", in September 2023, promoting it through various channels to enhance GenAI literacy among students and faculty, which also created a timely opportunity to conduct this study.

Ethical approval was secured from the university's research ethics committee prior to data collection. All procedures adhered to ethical standards, with informed consent obtained from all participants. Participants were selected using a convenience sampling method, targeting students in the disciplines of engineering, mathematics, and humanities and social sciences who had prior exposure to GenAI tools. In total, 347 students consented to participate in the quantitative phase of the study. Although the participants were from different year levels, they gained equal access to the institutional GenAI platform around the same period of time, providing a degree of homogeneity across the sample. For the qualitative phase, a nested sampling approach (Creswell & Plano Clark, 2018) combined with maximum variation sampling (Dörnyei, 2007) was used to select 24 students, ensuring a diverse representation across disciplines and different levels of GenAI literacy.

Data Collection

Two primary instruments were utilised:

- **GenAI Literacy Scale**: Adapted from a validated ChatGPT literacy scale by Lee and Park (2024), this tool measures five dimensions of GenAI literacy: basic technical proficiency (4 items), communication proficiency (5 items), creative application (4 items), critical evaluation (6 items), and ethical competence (4 items). The scale was pilot-tested with 13 students to ensure contextual relevance and comprehensibility, following recommendations by de Vaus (2014). Modifications included rewording items to reference locally available GenAI tools and adding clarification notes in Chinese. Appendix A presents the full version of the adapted 5-point GenAI literacy scale. Participants completed the 23-item questionnaire within approximately 10 minutes. The scale's validity and reliability were further assessed via statistical analyses, with the results reported in the Results section.
- **Semi-structured Interviews**: Conducted in Chinese, these interviews complemented the quantitative data by providing deeper insights into students' perceptions of their GenAI literacy. The interview protocol aligned with the theoretical dimensions of the GenAI literacy scale and is detailed in Appendix B. The interviews lasted between approximately 20 and 40 minutes, with an average of 30 minutes.

The questionnaire participant sample was recruited to align with the study's research questions and to ensure meaningful comparisons across disciplinary backgrounds. Specifically, students ($n = 347$) were drawn from three academic areas within the EMI institution: engineering ($n = 157$), mathematics ($n = 103$), and humanities and social sciences ($n = 87$), making them relevant for investigating disciplinary variations in GenAI literacy (RQ1). The total sample size of 347 students was sufficient for conducting latent profile analysis (RQ2), which requires a relatively large and heterogeneous sample to detect underlying subgroups (Nylund et al., 2007). To explore students' self-perceptions (RQ3), 24 participants from the three disciplines were selected for semi-structured interviews, ensuring disciplinary diversity. Overall, the sampling strategy aimed to achieve both representativeness within the EMI context and variation across disciplines, thereby enhancing the interpretability and relevance of the findings. The limitations related to sampling methods and potential biases are acknowledged, with impacts on the study's findings discussed in the subsequent sections.

Data Analysis

Quantitative data were analysed using IBM SPSS Statistics 27 and Mplus. The GenAI literacy scale underwent exploratory factor analysis (EFA) and reliability testing via Cronbach's alpha. Convergent and discriminant validity assessments were also conducted to ensure the robustness of the measurements.

For RQ1, disciplinary differences in GenAI literacy were examined using a Kruskal-Wallis test. This nonparametric test was used to examine group differences in GenAI literacy scores across disciplines, as it is a suitable alternative to the parametric ANOVA test that does not assume homogeneity of variances or interval-level data (Field, 2024; McKight & Najab, 2010). Although the GenAI literacy scores were normally distributed based on the skewness and kurtosis values checked, the use of a nonparametric method provided a more conservative and appropriate approach to answer RQ1.

RQ2 involved a multigroup latent profile analysis (LPA) to identify distinct GenAI literacy profiles among students. LPA is a person-centred statistical approach that identifies latent profiles within a population based on a specific set of variables (Spurk et al., 2020). Multigroup LPA extends traditional LPA by allowing profile identification across different groups based on statistical fit parameters (Morin et al., 2016). Unlike cluster analysis, which groups individuals based on observed similarity (Adachi, 2020), LPA provides a more statistically rigorous approach by identifying latent profiles through model fit indicators, yielding more meaningful and interpretable profiles based on underlying score patterns (Oberski, 2016). The optimal number of profiles was determined using multiple model fit indices, including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), where lower values indicate a better model fit. The entropy value was also examined, as higher entropy (> 0.80) suggests a more distinct classification of profiles. The bootstrapped likelihood ratio test (BLRT) p-value was checked, with $p < 0.05$ indicating a better fit than the previous profile solution (Akogul & Erisoglu, 2017).

For RQ3, qualitative data from interviews were analysed using reflexive thematic analysis as per Braun and Clarke (2022). To systematically explore EMI students' perceived GenAI literacy, the main thematic categories were deductively derived from the five core theoretical dimensions. Sub-themes were then inductively generated based on repetitive codes, iteratively revised, and refined through multiple rounds of coding. The final themes were structured and synthesised for further analysis. Following Braun and Clarke's (2022) guidelines, the reliability of the qualitative data analysis was enhanced through continuous researcher reflexivity and collaborative discussions to ensure analytical rigour.

Results

Validation of the GenAI Literacy Scale

Before conducting EFA on the dataset (n = 347), assumptions were checked to ensure its appropriateness. The application of EFA was deemed suitable, as the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy value was 0.92, indicating excellent sampling adequacy (Field, 2024). Additionally, Bartlett's Test of Sphericity yielded a significant result ($p = 0.000$). The assumption of normality was satisfied, with all skewness values falling within the acceptable range of -1 to +1 and kurtosis within -2 to +2 (Hair et al., 2019). The common factor model with 23 items was estimated using the maximum likelihood (ML) method. Oblique Promax rotation was applied, as it allows for more flexible and interpretable solutions. Following Hair et al.'s (2019) recommendation, only items with a factor loading exceeding 0.50 were retained for interpretation. Setting eigenvalues greater than 1 as the retention criterion, the EFA results identified the existence of five factors (see Table 2). The goodness-of-fit indices were significant ($p = 0.000$), supporting the appropriateness of this factor structure. Furthermore, the scree plot test confirmed the need to retain the five factors (see Figure 1).

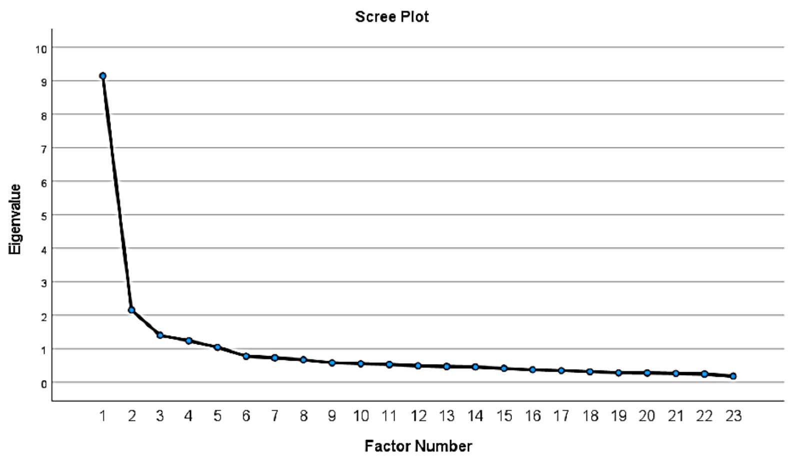

Figure 1. EFA scree plot

The ML EFA results showed that four items (items 4, 13, 19, and 23) from the basic technical proficiency, creative application, critical evaluation, and ethical competence subscales, respectively, did not cluster as expected after rotation. Hence, these four items were removed, leaving 19 retained items. The remaining items aligned well with their respective theoretical dimensions, providing empirical evidence for content validity. Following the EFA validation, Cronbach's alpha (α) was calculated to assess the internal consistency of the 19-item GenAI literacy scale. The overall scale demonstrated high reliability (α = 0.918), exceeding the commonly accepted 0.70 threshold. Each of the five subscales also exhibited high internal consistency (see Table 2), further affirming the scale's reliability.

Table 2. ML EFA results (n = 347)

Factor (F) loading							Cronbach's alpha
Sub-scale	**Item**	**F1**	**F2**	**F3**	**F4**	**F5**	
1. Basic technical proficiency	Item 1				.769		.786
	Item 2				.877		
	Item 3				.556		
	Item 4						
2. Communication proficiency	Item 5	.850					.895
	Item 6	.944					
	Item 7	.849					
	Item 8	.575					
	Item 9	.604					
3. Creative application	Item 10					.721	.818
	Item 11					.680	
	Item 12					.880	
	Item 13						
4. Critical evaluation	Item 14		.793				.854
	Item 15		.817				
	Item 16		.835				
	Item 17		.720				
	Item 18		.596				
	Item 19						
5. Ethical competence	Item 20			.759			.795
	Item 21			.850			
	Item 22			.645			
	Item 23						

In addition, the convergent validity of the five sub-scales was evaluated using composite reliability (CR) and average variance extracted (AVE). Convergent validity is established when CR values are greater than 0.70, and AVE values surpass 0.50 (Hair et al., 2019). Since all sub-scales met these criteria (see Table 3), the GenAI literacy scale demonstrated strong convergent validity.

Table 3. Convergent validity results (n = 347)

Sub-scale	CR	AVE
1. Basic technical proficiency	0.78	0.56
2. Communication proficiency	0.88	0.61
3. Creative application	0.81	0.59
4. Critical evaluation	0.87	0.57
5. Ethical competence	0.80	0.57

Discriminant validity was assessed using the Fornell and Larcker (1981) criterion, which requires that the square roots of the AVE values (shown along the diagonal axis) exceed the corresponding inter-construct correlation coefficients. As shown in Table 4, all five sub-scales met this requirement, confirming discriminant validity. Therefore, based on the convergent and discriminant validity results, all 19 items were retained in the GenAI literacy scale for further data analysis.

Table 4. Discriminant validity results (n = 347)

Sub-scale	Sub-scale 1	Sub-scale 2	Sub-scale 3	Sub-scale 4	Sub-scale 5
1. Basic technical proficiency	**0.75**				
2. Communication proficiency	0.61	**0.78**			
3. Creative application	0.34	0.57	**0.77**		
4. Critical evaluation	0.49	0.62	0.55	**0.75**	
5. Ethical competence	0.69	0.60	0.47	0.55	**0.75**

GenAI Literacy Differences by Discipline

To address RQ1, the Kruskal-Wallis test was conducted to examine whether there were statistically significant differences in GenAI literacy across three disciplinary groups: engineering, humanities and social sciences, and mathematics. The results (see Table 5) revealed a significant difference in overall GenAI literacy levels among the disciplines, $H(2) = 25.65$, $p < .001$, $\eta 2 = 0.07$, indicating a medium effect size based on the thresholds (0.01 = small, 0.06 = medium, and 0.14 = large) suggested by Ellis (2010) and Cohen (1988). Post hoc pairwise comparisons further indicated that engineering students had significantly higher GenAI literacy than their peers in humanities and social sciences ($p = .000$) and mathematics ($p = .000$). However, no significant difference was observed between students in humanities and social sciences and those in mathematics ($p = 1.000$).

These findings were consistent across the four dimensions of GenAI literacy: basic technical proficiency, communication proficiency, creative application, and critical evaluation, with engineering students outperforming their peers in all these areas, and effect sizes ranging from small to medium (see Table 5). In contrast, no significant difference was found in ethical competence among students from the three disciplines. This suggests that engineering students possess a more advanced level of GenAI literacy, particularly in the technical, communicative, creative, and evaluative aspects. The lack of significant variation in ethical competence across disciplines points to a common baseline understanding or similar educational exposure to the ethical issues related to GenAI use.

Table 5. Kruskal-Wallis test results of disciplinary differences in GenAI literacy (n = 347)

	Discipline	n	Mean rank	H	df	p	$\eta 2$	Differences
Overall GenAI literacy	G1	157	203.95	25.65	2	<.001	0.07	G1-G2*** (p = .000)
	G2	87	147.06					G1-G3*** (p = .000)
	G3	103	151.11					G2-G3 (p = 1.000)
Basic technical proficiency	G1	157	203.82	27.55	2	<.001	0.07	G1-G2*** (p = .000)
	G2	87	138.39					G1-G3** (p = .001)
	G3	103	158.64					G2-G3 (p = .490)
Communication proficiency	G1	157	200.65	21.36	2	<.001	0.06	G1-G2*** (p = .000)
	G2	87	144.36					G1-G3** (p = .003)
	G3	103	158.42					G2-G3 (p = 1.000)
Creative application	G1	157	195.28	13.28	2	.001	0.03	G1-G2** (p = .004)
	G2	87	152.82					G1-G3* (p = .014)
	G3	103	159.45					G2-G3 (p = 1.000)
Critical evaluation	G1	157	197.71	16.14	2	<.001	0.04	G1-G2** (p = .004)
	G2	87	155.17					G1-G3** (p = .002)
	G3	103	153.77					G2-G3 (p = 1.000)
Ethical competence	G1	157	184.43	4.31	2	.116	0.01	
	G2	87	173.93					
	G3	103	158.17					

Note: G1 = Engineering, G2 = Humanities and Social Sciences, G3 = Mathematics, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

GenAI Literacy Profiles Across Disciplines

To address RQ2, a multigroup LPA was conducted to identify the GenAI literacy profiles among EMI engineering (n = 157) and non-engineering (n = 190) students, with this categorisation informed by the disciplinary differences observed in RQ1. Based on the model fit indices presented in Table 6, the model with three profiles was identified as the best solution (Akogul & Erisoglu, 2017). Therefore, multigroup LPA, based on the mean scores of GenAI literacy, revealed three distinct learner profiles: Foundational Learners, Balanced Practitioners, and Proficient Achievers (see Figure 2). Table 7 shows the descriptive data for GenAI literacy in each profile.

First, the Foundational Learners exhibited the lowest levels of GenAI literacy across all five dimensions, indicating that their competencies in this area are still underdeveloped. They demonstrated only a basic grasp of GenAI-related skills, with creative application being the weakest dimension for both engineering (mean = 2.72) and non-engineering students (mean = 2.11). Additionally, non-engineering students showed limited technical proficiency (mean = 2.25), suggesting a minimal familiarity with GenAI tools and their applications. However, within the five dimensions of AI literacy, critical evaluation emerged as their strongest competence (mean = 2.96 for engineering, 2.59 for non-engineering). This group likely lacks confidence and trust in utilising AI technologies and may require foundational training to enhance their GenAI literacy.

Second, the Balanced Practitioners were well-rounded learners who displayed moderate proficiency across all five dimensions. This profile consists of about half of the investigated body, with approximately 24.8% of engineering students and 32.3% of non-engineering students. Their strongest competency was communication proficiency, with mean scores of 4.05 for engineering students and 3.54 for non-engineering students, indicating their ability to effectively communicate and engage with GenAI tools. However, basic technical proficiency (mean = 3.47 for engineering, 2.90 for non-engineering) and ethical competence (mean = 3.09 for engineering, 2.98 for non-engineering) were the weakest areas of both engineering and non-engineering students, suggesting that they may still face challenges with more advanced AI applications and ethical considerations in AI contexts.

Third, the Proficient Achievers represented the most advanced group, demonstrating high levels of GenAI literacy across all five dimensions. Similar to the Balanced Practitioners, they excelled the most in communication proficiency but the least in technical and ethical competence. This group is well-equipped to leverage GenAI tools effectively but may need further guidance in technical knowledge and ethical considerations to ensure informed and responsible decision-making.

Table 6. Model fit indices for latent profile solutions

Number of profiles	Profile size	LogLik	AIC	BIC	Entropy	BLRT_p
1	347	-2546.17	5124.34	5185.93	1.00	
2	205, 142	-2373.40	4800.80	4904.74	0.87	0.000
3	55, 198, 94	-2309.02	4694.05	4840.33	0.87	0.000

Note: LogLik log-likelihood, *AIC* Akaike information criterion, *BIC* Bayesian information criterion, *BLRT_p p*-value for the bootstrapped likelihood ratio test

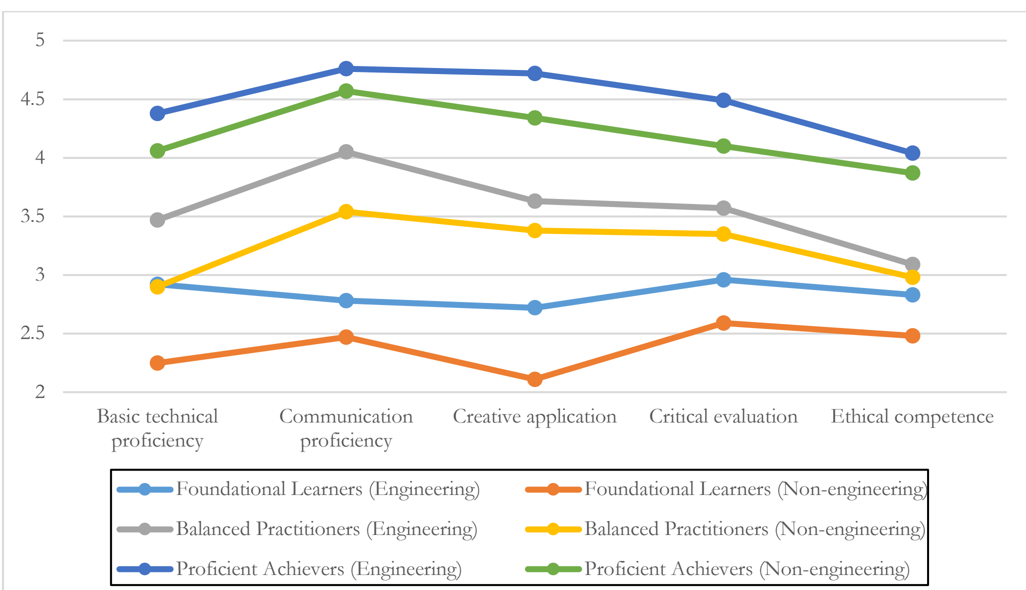

Figure 2. GenAI literacy profiles of EMI engineering and non-engineering students

Table 7. EMI students' GenAI literacy in the three profiles (n = 347)

	Profile 1: Foundational learners (n = 55)				Profile 2: Balanced practitioners (n = 198)				Profile 3: Proficient achievers (n = 94)			
	Engineering (n = 25) Probability: 86.3%		Non-engineering (n = 30) Probability: 91.4%		Engineering (n = 86) Probability: 89.5%		Non-engineering (n = 112) Probability: 90.5%		Engineering (n = 46) Probability: 89.1%		Non-engineering (n = 48) Probability: 91.2%	
	Mean (S.E.)	*p*	Mean (S.E.)	*p*	Mean (S.E.)	*p*	Mean (S.E.)	*p*	Mean (S.E.)	*p*	Mean (S.E.)	*p*
Basic technical proficiency	2.92 (0.28)	0.000	2.25 (0.26)	0.000	3.47 (0.32)	0.000	2.90 (0.10)	0.000	4.38 (0.15)	0.000	4.06 (0.14)	0.000
Communication proficiency	2.78 (0.71)	0.000	2.47 (0.18)	0.000	4.05 (0.20)	0.000	3.54 (0.14)	0.000	4.76 (0.09)	0.000	4.57 (0.11)	0.000
Creative application	2.72 (0.26)	0.000	2.11 (0.26)	0.000	3.63 (0.33)	0.000	3.38 (0.13)	0.000	4.72 (0.13)	0.000	4.34 (0.16)	0.000
Critical evaluation	2.96 (0.17)	0.000	2.59 (0.25)	0.000	3.57 (0.26)	0.000	3.35 (0.08)	0.000	4.49 (0.19)	0.000	4.10 (0.14)	0.000
Ethical competence	2.83 (0.23)	0.000	2.48 (0.24)	0.000	3.09 (0.17)	0.000	2.98 (0.10)	0.000	4.04 (0.35)	0.000	3.87 (0.20)	0.000

EMI Students' Perceptions of Their GenAI Literacy

To answer RQ3, the interview findings shed light on how EMI students perceive their GenAI literacy. Representative excerpts, labelled with participants' fake identifications and their specific disciplines, are presented below.

Overall, all interviewees highlighted the positive impact of GenAI on enhancing the efficiency of their disciplinary learning and alleviating the challenges of studying through EMI. For example, one student shared the benefits of using GenAI in multiple aspects:

> *For terminologies, AI can explain the meaning of words and provide example sentences to help me understand better. For grammar, AI can give me examples of how to use certain structures. For reading, it can extract key information to help me understand the text and also assist with translation, allowing me to learn new words and phrases in the process. For writing, AI can teach me a variety of sentence patterns to enrich both the content and form of my essays.* (Participant 4, engineering).

Similar advantages were also reported by other students (e.g., Participants 1, 4, and 5, humanities and social sciences; Participants 5, 8, and 9, engineering). Participant 4 (humanities and social sciences) noted that "*By interacting with AI, I can practise speaking and writing in a pressure-free environment, which helps boost my confidence.*" However, several students raised concerns about a potential decline in English language abilities. As one expressed,

> *It has weakened my ability to read academic literature and look up vocabulary on my own. I might be more inclined to just feed the text into AI and let it translate for me, rather than reading the English articles myself and improving my ability to learn through English. If I want to write something in English, I might rely on AI to generate a paragraph with the right words, especially if I want to paraphrase something. I think this isn't very helpful for my English learning because ideally, I should be doing the paraphrasing myself.* (Participant 8, engineering).

These reflections underscore both the supportive and potentially limiting effects of GenAI on EMI students' independent learning and language development.

Focusing on self-perceived GenAI literacy, the interview data revealed insights into students' technical proficiency with GenAI tools, particularly in terms of their foundational knowledge and ability to use the models. Engineering students demonstrated a solid understanding of basic AI principles, which they believed contributed to more accurate and efficient responses. As one student explained:

> *I have learned some basic AI theories and have a general understanding of its principles. So, when I use it, I provide a lot of context, which makes the generated answers more accurate and improves efficiency. It's important to first understand how generative language models work – not necessarily mastering the entire technology, but at least knowing the general approach they take. This helps us use the technology more effectively.* (Participant 6, engineering)

Engineering students also showed their understanding of different AI models; for example, "*Different questions to different AI models yield varying levels of accuracy. ChatGPT is more versatile, while Claude excels in scientific and technical areas. GPT-4, 4.0, and 3.5 each have different strengths and approaches. If you can leverage their strengths and avoid their weaknesses, it could make personal use more efficient*" (Participant 6, engineering). In contrast, some non-engineering students expressed uncertainty when using various AI models, stating, *"I will try asking the same question to different AI models, and the results may be different. This sometimes makes me feel confused, as I don't know which answer is correct or incorrect."* (Participant 24, mathematics). This disparity aligns with the quantitative findings showing engineering students possess stronger competencies in AI technologies, suggesting that non-engineering students may benefit from additional guidance on understanding basic AI principles and selecting appropriate AI models for specific tasks.

Regarding communication proficiency, students highlighted the importance of effective prompting strategies to maximise AI's usefulness. Some engineering students adopted a step-by-step approach when interacting with AI, as one student noted, *"Address one small issue at a time instead of asking a large, complex question right away. Break it down into smaller questions and ask one by one"* (Participant 1, engineering). Similarly, one non-engineering student described their prompting approach as *"I usually ask AI questions from a broad perspective, gradually narrowing them down to specific details. I start with a general question and then break it down step by step, which helps AI generate more accurate answers"* (Participant 18, humanities and social sciences).

Additionally, engineering students appeared to employ more advanced prompting strategies, such as following persona patterns or including detailed contextual information and delimiters, which echoes the quantitative findings indicating their higher communication proficiency in using GenAI tools. For instance:

> *If I need to ask a question in a specific field, I can start the conversation by giving the AI a persona, like an expert who is very familiar with a certain project or area.* (Participant 3, engineering)
>
> *When giving prompts, you must provide some background, such as relevant social issues, and set limits like word count. You need to clearly communicate your requirements to the AI; otherwise, it may not generate what you want.* (Participant 4, engineering)

As for creative application, while two students noted limited creative use of GenAI beyond daily life and learning queries, others reported using it for different scenarios, such as creating photos, advertisements (Participant 2, engineering), logos (Participant 7, engineering), music (Participant 13, humanities and social sciences), and co-writing (Participant 24, mathematics). Students also discussed the role of GenAI in fostering creativity, particularly in terms of inspiring new ideas. Engineering students highlighted AI's potential for creative thinking; as one student noted, *"Creativity often requires inspiration. Interacting with AI can help me think from different perspectives and enhance my creative thinking … It sparks new ideas in me"* (Participant 10, engineering). Non-engineering students also found AI useful for exploring alternative viewpoints. One student exemplified, *"For a linear algebra problem, initially, I* *couldn't figure it out from the matrix perspective, so I asked AI. It explained the problem using determinants, and suddenly, everything clicked for me. By answering from a perspective that I hadn't considered before, AI helped me unlock a new way of thinking, allowing me to follow its reasoning and explore further"* (Participant 19, mathematics). This suggests that both groups of students recognised AI's potential in creative applications. Noticeable differences were not observed in the qualitative data, likely due to the small effect size of the statistical difference between disciplinary groups.

In terms of critical evaluation, all interviewees recognised the need to evaluate AI's output. The interview data revealed different evaluation strategies depending on the issues students encountered. For more complex or important matters, students emphasised the need to verify AI-generated responses with credible sources: *"For academic reports, after asking AI, I might check relevant official websites or databases such as China National Knowledge Infrastructure to verify the information"* (Participant 2, engineering); *"When writing essays for disciplinary subjects, I'll definitely verify the information because I need to take responsibility for what I write"* (Participant 13, humanities and social sciences). On the other hand, when dealing with relatively unimportant matters or simpler questions, the interviewees expressed less need for evaluation, indicating their trust in GenAI outputs to some extent: *"For relatively unimportant matters, I don't evaluate whether AI-generated content is correct or not – I choose to trust it"* (Participant 10, engineering); *"Sometimes I directly adopt AI's answers, especially for simpler questions where its response is clear and professional. In such cases, I don't feel the need to further check its credibility"* (Participant 13, humanities and social sciences). More importantly, the findings highlight the importance of having essential prerequisite subject knowledge in order to critically evaluate AI's output. As one student noted, *"It's still important to attend classes and learn properly. After all, when asking AI, we can't be completely clueless. We need to have some foundational knowledge before seeking help from AI"* (Participant 1, engineering). Despite the small-to-medium statistical differences, interviewees across disciplines demonstrated awareness of critical evaluation when engaging with GenAI tools.

Concerning ethical competence, students discussed concerns about academic integrity, data privacy, and copyright issues. Students were aware of the ethical risks of AI-assisted academic work. As two interviewees noted, *"If some assignments are entirely completed with AI assistance, it would violate academic integrity. Similarly, secretly using AI in online exams is undoubtedly considered cheating, which is an act against academic ethics"* (Participant 7, engineering); *"For majors in humanities and social sciences, assessments are usually in the form of essay writing. However, it is clear that we cannot use AI to generate essays"* (Participant 18, humanities and social sciences). Concerns about data and user privacy were also raised: *"We need to consider whether the uploaded data will be stored in the AI's database, as there is a risk that the data might be made public"* (Participant 1, engineering); *"I believe user privacy protection needs to be considered, as it helps prevent personal information from being used for improper purposes"* (Participant 16, humanities and social sciences). Furthermore, concerns about copyright focused on the use of data and content generated by AI: *"AI may infringe on others' intellectual property rights. Many things require authorisation before use, and if I use them directly without permission, it would actually be a violation of copyright"* (Participant 24, mathematics). These concerns match the quantitative findings, showing that students across disciplines are aware of the ethical implications of using GenAI tools.

DISCUSSION

DISCIPLINARY VARIATIONS IN EMI STUDENTS' GENAI LITERACY

The validation of the GenAI literacy scale confirmed its effectiveness in capturing five core dimensions of literacy – basic technical proficiency, communication proficiency, creative application, critical evaluation, and ethical competence – among EMI undergraduates. The robustness of the scale was supported by high KMO values, strong factor loadings, and excellent internal consistency across all subscales, consistent with best practices in psychometric validation (Field, 2024; Hair et al., 2019). The removal of poorly performing items and the results of both convergent and discriminant validity assessments underscore the reliability of the instrument and its suitability for use in diverse educational settings.

Building on this validated scale, the subsequent analysis revealed clear disciplinary differences in GenAI literacy. Engineering students outperformed their peers in basic technical proficiency, communication proficiency, creative application, and critical evaluation; however, no statistically significant difference was observed in ethical competence. These disparities were corroborated by qualitative data, which demonstrated that engineering students possessed more advanced knowledge of GenAI tools, a deeper understanding of AI model functionalities, and greater sophistication in prompt engineering. These findings likely reflect broader trends identified in the literature, where AI instruction is often embedded in technology-oriented programmes such as computer science and engineering but remains marginal or absent in other disciplines (Cantú-Ortiz et al., 2020; Kandlhofer et al., 2016; Ng et al., 2023).

Notably, the findings of this study advance prior theories by revealing that AI literacy is not uniformly distributed within the STEM stream. Though typically categorised within STEM, mathematics students did not differ significantly from students in the humanities and social sciences. This may relate to the limitations of GenAI in numerical problem-solving, which has historically undermined its relevance in quantitative subjects (Valeri et al., 2025). The observed parity suggests that GenAI integration is shaped less by disciplinary classification and more by how well AI tools align with a subject's pedagogical focus. This nuance highlights the need to rethink AI adoption strategies not only across STEM/non-STEM divides but also within STEM disciplines where technical alignment may be weak.

The finding of no significant differences in ethical competence across disciplines is also worth highlighting. This contrasts with Qu et al. (2024) and Raman et al. (2024), who found that social sciences students face more ethical dilemmas with GenAI than their engineering peers, largely due to internal values related to authenticity and academic integrity. It also challenges the assumption that engineering students, particularly those in computer science, might demonstrate higher ethical competence due to their exposure to ethical considerations in the AI design and development (Long & Magerko, 2020). Interview data from this study revealed a broad awareness of issues such as academic integrity, data privacy, and copyright across all examined disciplines, consistent with previous research suggesting that such ethical concerns are commonly shared among students, regardless of their disciplinary background (McMurtrie, 2023). This may reflect a general cultural sensitivity to ethical issues in digital spaces, or possibly the influence of informal norms and general university-level messaging, even in the absence of specific institutional policies. The consistency in ethical awareness stands in contrast to the variability observed in more applied dimensions of GenAI literacy.

More crucially, the intersection of GenAI literacy, disciplinary backgrounds, and English language proficiency presents a complex dynamic in shaping students' experiences within EMI contexts. While English proficiency has long been recognised as a crucial factor for EMI academic success (Rose et al., 2020; Xie & Curle, 2022), the emergence of GenAI offers new opportunities to mitigate the language-related challenges faced by students (e.g., Hong, 2022; Mai & Van Hanh, 2024). GenAI tools, as revealed by the interview data, support tasks such as reading comprehension, writing development, and terminology acquisition, which can potentially enhance EMI students' academic performance. However, the observed disciplinary disparities in GenAI literacy raise concerns about equitable access to these benefits. Students in fields with higher GenAI proficiency may be better positioned to achieve stronger academic outcomes, highlighting the need for pedagogical adjustments. Furthermore, as students increasingly rely on GenAI tools to mediate language barriers and access disciplinary knowledge, the role of English proficiency in EMI contexts is becoming more complex. EMI has traditionally been viewed as a "killing two birds with one stone" approach (Curdt-Christiansen et al., 2023), offering dual benefits of content knowledge acquisition and English language development (Hu & Wu, 2020; Kim et al., 2017). However, the growing use of GenAI raises important questions about whether this secondary benefit of improving English proficiency is being diminished, as students may no longer feel the need to actively develop their language skills to engage with academic content.

Pedagogical Implications for GenAI Literacy Across Disciplines and Learner Profiles

The observed disciplinary variations and distinct GenAI literacy profiles offer valuable pedagogical insights. Firstly, the results suggest that disciplinary context is a powerful determinant of students' GenAI capabilities, supporting the view that literacy in emerging technologies is not simply a matter of individual interest but is shaped by systematic opportunities and constraints. These findings align with broader calls in the literature for a more inclusive and embedded model of AI literacy development in higher education (Kelly et al., 2023; Southworth et al., 2023). Practically, the evidence points to an urgent need to integrate GenAI instruction beyond traditional engineering and computer science programmes. Institutions should prioritise embedding AI-related learning outcomes into subject-specific modules across the curriculum, with attention to relevance, application, and accessibility. Such an approach would allow students from all disciplines to develop baseline AI literacy while enabling differentiated pathways for deeper engagement.

Secondly, the identification of three GenAI literacy profiles – Foundational Learners, Balanced Practitioners, and Proficient Achievers – further reinforces the value of targeted pedagogical strategies. Foundational Learners, who scored lowest across all dimensions, represent a group that may be unfamiliar with GenAI or uncertain about its utility. For these students, early exposure to AI tools through structured, low-barrier activities such as workshops or embedded coursework could help demystify AI and improve engagement. Initiatives like the AI Across the Curriculum movement at the University of Florida offer a promising model (Southworth et al., 2023). These should be complemented by problem-based learning and discipline-relevant applications to strengthen confidence (Kelly et al., 2023; Krakowski et al., 2022). In addition, despite their lower overall scores, Foundational Learners showed comparatively stronger performance in critical evaluation, echoing Beckman et al.'s (2025) findings that students with lower AI literacy tended to approach the technology more carefully. This pattern may reflect a cautious approach to GenAI, consistent with research highlighting the importance of trust in shaping AI adoption (Kelly et al., 2023; Ma, 2024). While critical engagement is essential, excessive scepticism could also inhibit learning and innovation. Building trust – through transparent use cases, scaffolded tasks, and opportunities for guided experimentation – could therefore support more balanced development.

Balanced Practitioners and Proficient Achievers, who made up the majority of the sample, exhibited strong communication proficiency but relatively lower scores in technical and ethical competence. These findings align with studies that suggest communication with GenAI can be effective even when users lack advanced technical knowledge (Knoth et al., 2024; Valeri et al., 2025). However, improving these students' understanding of how GenAI tools operate and the ethical challenges they may raise is essential for effective and responsible engagement. Pedagogical approaches for these students should focus on collaborative, project-based learning that involves working directly with GenAI tools in discipline-specific contexts (Ng et al., 2023). Ethical training should also move beyond general principles to explore field-specific dilemmas, using case studies that reflect real-world applications (Borenstein & Howard, 2021). These tailored interventions would not only address knowledge gaps but also foster a sense of ownership and accountability in GenAI use.

Conclusion

This study explored GenAI literacy across disciplines within an EMI university context, identified learner profiles, and examined students' self-perceptions of their GenAI competencies. Engineering students demonstrated significantly higher proficiency in technical, communicative, creative, and evaluative dimensions, while ethical competence remained consistent across disciplines. Three distinct GenAI literacy profiles were revealed: Foundational Learners, Balanced Practitioners, and Proficient Achievers. These findings highlight persistent disparities in students' AI competencies and emphasise the importance of addressing both disciplinary and learner-based differences in AI literacy development. The qualitative findings complemented and triangulated with the quantitative results.

The findings provide valuable insights into how GenAI literacy manifests across disciplines and student profiles in an EMI university. It highlights the uneven integration of GenAI into curricula, the differentiated needs of learners, and the importance of designing inclusive, context-aware educational strategies. Embedding GenAI literacy into non-engineering curricula is critical to closing disciplinary gaps. Simultaneously, recognising the diverse needs of Foundational Learners, Balanced Practitioners, and Proficient Achievers allows for more effective educational interventions. Basic skills training and problem-based learning are vital for underprepared students, while hands-on, discipline-specific, project-based learning experiences can help more advanced learners deepen their technical understanding and ethical awareness. As GenAI continues to transform academic practice, institutions must move beyond generic digital literacy models and commit to scalable, discipline-embedded, and learner-responsive approaches. Equipping students with the capacity to understand, apply, and question GenAI technologies is no longer optional; it is essential for supporting equitable academic success across disciplines in EMI settings. Additionally, the findings highlight the need to explore the evolving role of the English language in EMI education. As GenAI continues to mediate students' access to academic content, rethinking the role of the English language in EMI contexts becomes increasingly important.

A key strength of this study lies in its mixed-methods design and the successful validation of a context-sensitive GenAI literacy scale. The combination of quantitative and qualitative data offered a nuanced understanding of both the level and nature of students' GenAI literacy. However, the use of convenience sampling and the specificity of the EMI institutional context, where GenAI access is relatively structured, may limit the generalisability of the findings to other educational settings. Future research should consider stratified sampling across multiple institutions, regions, and cross-national contexts to capture a more representative picture of GenAI engagement and facilitate meaningful comparisons across educational systems. In addition, while the study focused on undergraduates, postgraduate students, and academic staff are also critical stakeholders in the AI literacy agenda. Investigating how these groups engage with GenAI could provide valuable comparative insights. More importantly, the identification of learner profiles also raises new questions about movement between profiles over time and the kinds of interventions that support such transitions. Longitudinal studies and action research involving instructional design experiments could help clarify how GenAI literacy evolves and what pedagogical strategies are most effective for supporting growth. As GenAI continues to shape teaching and learning, universities must adopt more responsive, inclusive strategies for developing students' AI literacy. This study offers a foundation for designing such approaches and supporting equitable engagement with AI across the curriculum.

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APPENDIX A. *GENAI LITERACY SCALE*

Please rate how relevant each statement is to your experience on a scale from 1 to 5.

1. Not at all relevant	2. Slightly relevant	3. Somewhat relevant	4. Moderately relevant	5. Very relevant

Note: Examples of Generative AI tools include XIPU AI (university-based), ChatGPT (overseas), and 文心一言 (Chinese local).

Sub-scale/Item	**Retain or Delete**
Sub-scale 1: Basic technical proficiency	
1. I can understand how GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言) generate responses. 我可以理解生成式人工智能是如何生成回复内容的。	Retain
2. I can understand how GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言) work. 我可以理解生成式人工智能的工作原理。	Retain
3. I have the ability to use GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言) in conjunction with other tools or technologies. 我有能力把生成式人工智能和其他工具或技术结合使用。	Retain
4. I can compare and evaluate the functions of different GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我可以比较和评估不同生成式人工智能之间的功能性区别。	Delete
Sub-scale 2: Communication proficiency	
5. I can communicate effectively with GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我可以与生成式人工智能进行有效沟通。	Retain
6. I can ask appropriate and effective questions to GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我可以向生成式人工智能提出恰当且有效的问题。	Retain
7. I can use technical terms in conversations with GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我在与生成式人工智能对话时可以使用专业术语。	Retain
8. I can ask accurate questions to GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言) using rich vocabulary 我可以运用丰富的词汇向生成式人工智能准确提问。	Retain
9. I can elicit a response from GenAI tools (e.g., XIPU AI, ChatGPT, 文心一言) to suit a particular situation (e.g., answering questions related to a particular course). 我可以引导生成式人工智能针对特定情景进行回复(例如解答某课程学习中的疑惑)。	Retain
Sub-scale 3: Creative application	
10. I can use GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言) to generate new ideas or solutions. 我可以使用生成式人工智能生成新的想法或方案。	Retain
11. I can improve my creativity or innovation skills using GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我可以运用生成式人工智能来提高我的创造或创新能力。	Retain

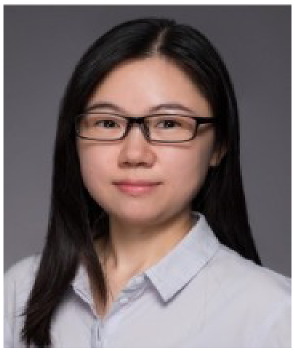
12. I can do creative writing using GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我可以运用生成式人工智能进行创意写作。	Retain
13. I can use GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言) to generate insights and trends on large datasets. 我可以运用生成式人工智能分析大型数据集，以此生成见解和趋势。	Delete
Sub-scale 4: Critical evaluation	
14. I can evaluate the accuracy of GenAI tools' (e.g. XIPU AI, ChatGPT, 文心一言) responses. 我可以评估生成式人工智能回复的准确度。	Retain
15. I can determine whether GenAI tools' (e.g. XIPU AI, ChatGPT, 文心一言) responses are true. 我可以确定生成式人工智能的回复是否属实。	Retain
16. I can evaluate the reliability of GenAI tools' (e.g. XIPU AI, ChatGPT, 文心一言) responses. 我可以评估生成式人工智能回复的可信度。	Retain
17. I can identify errors in GenAI tools' (e.g. XIPU AI, ChatGPT, 文心一言) responses. 我可以识别生成式人工智能回复中的错误。	Retain
18. I can evaluate the completeness of GenAI tools' (e.g. XIPU AI, ChatGPT, 文心一言) responses. 我可以评估生成式人工智能回复的完整性。	Retain
19. I can recognise and explain bias in GenAI tools' (e.g. XIPU AI, ChatGPT, 文心一言) responses (e.g., biases arising from socio-cultural or linguistic differences). 我可以识别并解释生成式人工智能回复中的偏颇(例如社会文化或语言差异带来的偏颇)。	Delete
Sub-scale 5: Ethical competence	
20. I can identify potential ethical issues (e.g., copyright) associated with the use of GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我会在使用生成式人工智能的过程中，识别出与其相关的潜在道德问题(例如知识产权问题)。	Retain
21. I can explore legal or ethical considerations (e.g., codes or guidelines) related to the use of GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我会在使用生成式人工智能的过程中，探索与其相关的法律或道德考量(例如阅读相关准则或指南)。	Retain
22. I can recognise potential privacy issues (e.g., data leakage) related to the use of GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言). 我会在使用生成式人工智能的过程中，识别出它带来的潜在隐私问题(例如数据泄露)。	Retain
23. I can use GenAI tools (e.g. XIPU AI, ChatGPT, 文心一言) ethically. 我能够有道德地使用生成式人工智能工具。	Delete

Appendix B. Semi-Structured Interview Protocol

1. What do you think about your technical proficiency in using GenAI tools? Why do you think so?
2. What do you think about your communication proficiency in using GenAI tools? Why do you think so?
3. Have you encountered difficulties when communicating with GenAI tools? If so, can you give an example?
4. Do you think you can use GenAI tools to improve creativity? Why do you think so?
5. Can you provide some examples of creative content generated by GenAI tools?

6. Do you evaluate the content generated by GenAI tools? If so, how do you do that? If not, why not evaluate?
7. What ethical considerations do you think are important when using GenAI tools? Why do you think so?

AUTHORS



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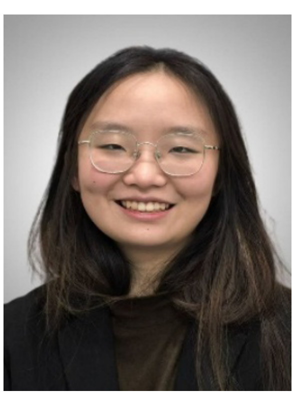

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