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STEM Undergraduates' Perceptions of AI Chatbots: A Cross-Sectional Descriptive Survey

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Abstract

We surveyed 297 STEM undergraduates at a single English-medium Sino–UK joint institution to document perceptions of AI chatbots for learning. Students reported high willingness to adopt AI chatbots (78%; 95% CI: 73.1–82.4) alongside concerns about over-reliance (67%; 95% CI: 61.4–72.1), content quality (52%; 95% CI: 46.2–57.5), and reduced human interaction (42%; 95% CI: 36.5–47.8). Over half (52%; 95% CI: 46.3–57.7) requested language/terminology support features, whereas only 16.8% reported language-related barriers. We attempted exploratory factor analysis and k-means clustering, but neither met the inclusion criteria; therefore, we report item-level frequencies only. The findings are descriptive and not generalisable (53% first-year, 80% male convenience sample). These patterns generate testable hypotheses about verification scaffolds, language support utility, and human–AI balance that warrant investigation through controlled studies.

Keywords: AI chatbots; STEM education; student perceptions; English-medium instruction; descriptive survey and EMI; survey research

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1. Introduction

Higher education—especially in Science, Technology, Engineering and Mathematics (STEM)—faces intensifying demands for scalable, personalised support while maintaining disciplinary rigour. Conversational AI systems ("AI chatbots") are increasingly embedded for clarification, feedback, and practice. Post-LLM studies report substantial uptake and generally positive attitudes toward their utility and ease of use (e.g., von Garrel & Mayer, 2023; Abdaljaleel et al., 2024; Albadarin et al., 2024), alongside persistent concerns about accuracy, depth, fairness, and appropriate use (Schei et al., 2024; Abbas et al., 2024). While institutional guidance has increased, many recommendations outpace fine-grained evidence about how students themselves appraise chatbot use in day-to-day coursework.

Two gaps are particularly salient. First, evidence of student perspectives within STEM and outside Western settings remains limited. Much of the literature synthesises general higher-education patterns or reports small, local implementations; less is known about how STEM undergraduates in English medium instruction (EMI) programmes for non-native speakers weigh benefits against risks in routine learning. Second, beyond global attitudes, we lack item-level descriptions of specific concerns and feature priorities—especially in EMI contexts where linguistic accessibility may shape perceived usefulness and comfort (Holmes et al., 2019).

Scope and aim: Because our sample is from a single site and is predominantly first-year, majority male, students, our aim is contextual documentation rather than general inference. We do not attempt cross-disciplinary comparisons, segmentation into student types, or confirmation of any latent factor structure. The results are descriptive within this cohort and are intended to generate hypotheses for future study.

Contributions (descriptive and context-bound).

1. Cohort baseline: Item-level documentation of willingness/comfort and perceived benefits in this single EMI cohort.
2. Concern frequencies: Item-level prevalence of specific concerns, highlighting over-reliance/learning dependency, content quality/accuracy, and reduced human interaction.
3. Language barriers vs. language supports: Clear distinction between a minority reporting language barrier concerns (~16.8%) and a majority requesting terminology/plain language supports (~52%), noting that the desire for clarifying tools does not necessarily imply a barrier.
4. Feature priorities: Documentation of what this cohort values in chatbot design (e.g., terminology support and follow-up questioning).

We do not test interventions; the practice considerations offered later are pilot ideas requiring prospective evaluation. A methodological note is provided in Methods: we attempted exploratory latent structure and clustering checks, but these did not meet the inclusion criteria and therefore are not used to support claims; we report item-level results only.

Section roadmap: Section 2 reviews the relevant literature on student use/perceptions of LLM chatbots, adoption constructs, and EMI considerations. Section 3 details the setting, instrument, and descriptive analysis approach (including decision gates that led us to report item-level results only). Section 4 presents the descriptive findings (willingness/comfort, benefits, concerns, and requested features). Section 5 discusses research questions arising from these patterns and study limitations. Section 6 concludes with contributions and priorities for validation and future research.

2. Literature Review

2.1. AI in Education: Current Landscape and Theoretical Foundations

Before the rise of generative AI, chatbots had shown promise in education, but the arrival of ChatGPT (GPT-3.5) in late 2022 triggered rapid shifts in how students engage with these tools. Recent evidence demonstrates substantial learning gains. Deng and Yu (2023) report significant effects on reasoning (d = 1.190) and achievement (d = 1.033) across 32 studies, while Abbas et al. (2024) warn of declines in engagement when reliance increases. UNESCO (2023), Department for Education [DfE], (2025), and the U.S. Department of Education, Office of Educational Technology (2024) each call for integration that supports human agency, trust, and equity. At the same time, longitudinal and multi-wave studies caution against over-reliance: initial engagement gains can be offset by procrastination and reduced performance when students substitute AI for core learning activities (Abbas et al., 2024). These mixed patterns underscore a central implementation challenge: how to translate efficacy from controlled studies into responsible, classroom-ready practices that preserve human agency and critical thinking. These tensions motivate a closer examination of how students themselves perceive the benefits and risks of LLM chatbots in STEM courses. In this study, we describe item-level patterns in one cohort; we do not test theoretical models or infer causal effects. Recent STEM-specific frameworks emphasise engagement and transdisciplinary integration as design constraints for classroom AI (León et al., 2025); here, we use such perspectives only as the interpretive context for descriptive patterns.

2.2. Chatbots in Educational Settings

Generative AI chatbots have shifted rapidly from experimental tools to everyday study aids. In higher education, students now report frequent use for clarification, idea generation, and drafting, with generally positive attitudes and notable cross-country consistency (e.g., Germany, the Middle East). Recent syntheses find broadly positive learning effects when use is structured and task-aligned, alongside persistent reservations about the reliability and depth of explanation (Albadarin et al., 2024; Abdaljaleel et al., 2024; Schei et al., 2024; von Garrel & Mayer, 2023). Pre-LLM syntheses have already highlighted timely feedback and personalisation alongside shallow dialogue and collaboration limits (Wollny et al., 2021; Smutny & Schreiberova, 2020; Kuhail et al., 2023; Pérez et al., 2020; Winkler & Söllner, 2018), and broader reviews of AI in higher education identified similar promise–risk patterns (Zawacki-Richter et al., 2019; Popenici & Kerr, 2017).

Emerging classroom studies suggest that pedagogy-first prompting and scoped use (e.g., worked-example guidance, formative checks) can unlock benefits while discouraging answer-copying (El Fathi et al., 2025). At the same time, longitudinal work warns that over-reliance can attenuate learning engagement and outcomes, underscoring the need to design for verification and student effort (Abbas et al., 2024). Guided by this literature, our instrument focused on perceived usefulness, comfort/willingness, concrete benefit domains, and concern items (accuracy, depth, over-reliance, and human interaction), as well as feature needs (language/terminology support and follow-up dialogue). Guided by this literature, our instrument focuses on willingness, comfort, perceived usefulness, concern items, and desired features; the results are purely descriptive within this cohort. Though from a different context (Serbian faculty), recent evidence suggests similar adoption patterns, with ChatGPT users reporting greater efficiency gains than non-users, yet both groups describe integration in teaching should be performed cautiously (Popović Šević et al., 2025).

2.3. Technology Adoption Frameworks

2.3.1. Models of Technology Acceptance

Classic acceptance models Technology Acceptance Model/Unified Theory of Acceptance and Use of Technology (TAM/UTAUT) remain useful lenses for generative AI tools when adapted to new constructs. Meta-analytic work shows that perceived usefulness and ease of use are strong, consistent predictors of intention in educational contexts (Scherer et al., 2019), while UTAUT highlights performance expectancy, effort expectancy, social influence, and facilitating conditions as key drivers (Venkatesh et al., 2003). Consistent with the Technology Acceptance Model, perceived usefulness and ease of use remain central correlates of intention (Davis, 1989), with meta-analytic evidence supporting TAM's robustness in educational contexts (Granić & Marangunić, 2019; Scherer et al., 2019). In generative AI settings, perceived intelligence and trust also matter. A 2024 study found that perceived intelligence mediates adoption pathways and that trust moderates core relationships, with implications for teaching students how and when to trust AI output (Shahzad et al., 2024). Trust and transparency were considered adoption-relevant correlates. While we do not test TAM/UTAUT hypotheses here, these models provide an interpretive context for our descriptive findings.

2.3.2. Diffusion and Integration Frameworks

Rogers' (2003) diffusion attributes (relative advantage, compatibility, complexity, trialability, observability) help explain why students are more likely to adopt chatbots that fit their course norms and study routines. The Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006) further argues that durable success requires coherence among technology, pedagogy, and content. These perspectives offer a background context institutions considering classroom implementation; in the present study, we report descriptive perceptions only and do not evaluate alignment or discipline-specific effects.

2.4. STEM-Specific Integration Challenges

STEM learning emphasises conceptual rigour and problem-solving; students judge tools by how well they support these tasks. Adoption is more likely when tools are compatible with disciplinary practices, embedded in assessment/feedback routines, and supported institutionally (Henderson et al., 2011). Instructor beliefs and classroom culture also play a significant role. Student-centred beliefs and clear facilitating conditions predict more extensive use, whereas scepticism and low confidence impede uptake (Ertmer & Ottenbreit-Leftwich, 2010; Tondeur et al., 2017). Against this backdrop, describing student perceptions—benefits, item-level concerns, and support needs—provides contextual insights into the realities of STEM study in this single cohort.

2.5. Student Use and Perceptions of LLM Chatbots

Since late 2022, large language models (LLMs) have rapidly transitioned from novelty to routine study support. Multi-country survey work shows substantial adoption among university students, with STEM cohorts often among the heaviest users (e.g., clarification of complex concepts, step-by-step troubleshooting, and drafting assistance) (von Garrel & Mayer, 2023; Abdaljaleel et al., 2024; Albadarin et al., 2024). Reported drivers of uptake map to familiar acceptance constructs, including perceived usefulness, ease of use, and social/instructor endorsement, which consistently predict the intention to use (Abdaljaleel et al., 2024).

Alongside uptake, recurrent concerns have stabilised across LLM-era studies: (i) accuracy/reliability and the need to verify model outputs; (ii) risks of over-reliance that could displace independent problem-solving; and (iii) possible erosion of human interaction (e.g., reduced instructor or peer engagement). Emerging longitudinal and synthesis work prompts caution that frequent, unstructured use can co-occur with procrastination or shallow strategies (e.g., Abbas et al., 2024; Schei et al., 2024). These patterns motivate instruments that capture willingness and comfort, perceived usefulness in core learning tasks, and concern items covering reliability, dependence/integrity, and human interaction, with open-ended prompts included to surface unanticipated issues. The present study aligns with this agenda by conducting a cross-sectional survey with embedded open-ended items on profile use, perceptions, and concerns among STEM undergraduates in a transnational, English-medium context (see Appendix E for the full item wording and anchors). The results are descriptive within this cohort and not generalisable.

2.6. Policy and Institutional Frameworks

Since late 2022, policy guidance has proliferated. UNESCO (2023) emphasises human agency, inclusion, and governance for generative AI in education; the Department for Education [DfE] (2025) provides institution-level guidance on teaching, assessment, and integrity; and the U.S. Department of Education, Office of Educational Technology (2023) highlights equity and human-centred use, followed by a 2024 developer guide that stresses transparency, evidence, and educator oversight. Earlier UNESCO work similarly framed opportunities and risks for AI in education, highlighting governance and capacity-building (Pedro et al., 2019). The implications of UNESCO (2023), Department for Education [DfE] (2025), and U.S. Department of Education, Office of Educational Technology (2024) call for AI in education to uphold transparency (through source disclosure and apparent limitations), integrity (through appropriate-use boundaries), and human-centred learning (through instructor presence and peer interaction). In our analysis, such policy tenets are used only as an interpretive context for descriptive student perceptions.

Faculty perspectives from other contexts echo these policy concerns: Serbian academics report insufficient institutional guidance regardless of ChatGPT use, suggesting implementation gaps may transcend specific settings (Popović Šević et al., 2025).

2.7. Equity, Ethics, and Language Accessibility

Policy guidance converges on the importance of human agency, inclusion, and integrity in AI education. In English-medium, non-native contexts, this translates into concrete needs around language support, equitable access, and clarity on appropriate use (UNESCO, 2023; Department for Education [DfE], 2025; U.S. Department of Education, Office of Educational Technology, 2024). Accordingly, our survey included items on language/terminology support, privacy/integrity concerns, and acceptable-use boundaries. This enabled us to determine how these items co-occur with reported willingness in this cohort; we do not infer causality. In EMI contexts, language needs intersect with cultural norms around authority and respect in classroom discourse (Hofstede, 2001); our survey did not measure these constructs, so we treat them only as background considerations.

Related faculty evidence indicates that adoption depends not only on tool capabilities but also on organisational supports and governance (Popović Šević et al., 2025).

2.8. Research Gaps and Study Rationale

Despite accelerating adoption, four evidence gaps remain:

1. Student-perspective evidence in STEM outside Western-majority contexts.
2. Item-level documentation of concerns and feature requests from single cohorts.
3. Empirical attention to the distinction between language barriers and language-support needs.
4. Transparent reporting of descriptive patterns with appropriate limitations.

To address these gaps, we conducted a cross-sectional survey with embedded open-ended items among STEM undergraduates at a Sino–UK joint institution, reporting descriptive, item-level patterns with complete transparency about scope limitations. Throughout, we avoid persona or factor claims and do not make between-discipline inferences; subsequent sections report item-level descriptives with appropriate caveats.

3. Materials and Methods

3.1. Research Design and Context

We employed a cross-sectional survey with embedded open-ended items to describe how STEM undergraduates perceive and intend to use AI chatbots for learning in a single institutional setting. The study took place at the SWJTU–Leeds Joint School (Southwest Jiaotong University) in Chengdu, China—an English-medium, transnational engineering programme. Participants were recruited via convenience sampling across Electronic and Electrical Engineering (EEE), Computer Science (CS), Civil Engineering with Transport (CET), Materials Science and Engineering (MSE), and Mechanical Engineering (ME). Because this is a single-site convenience sample that over-represents first-year and male students, we make no claims of representativeness or generalizability—even within our institution. Quantitative analyses are limited to item-level descriptive statistics (with 95% confidence intervals) and a small set of within-cohort correlations among acceptance items. We do not conduct between-group inference, confirm latent factor structures, or segment students into personas; any exploratory multivariate attempts that did not meet inclusion criteria are noted for transparency and not carried forward. Open-ended responses were analysed inductively to provide contextual themes that complement the descriptive survey patterns.

3.2. Participants and Sampling

Undergraduates were recruited via convenience sampling from large-enrolment STEM courses during Spring 2025. The final analytic sample comprised N = 297 Chinese students enrolled in an English-medium programme (Table 1). This snapshot—largely first-year and majority male, with very few seniors—cannot represent the whole trajectory of undergraduate experiences, even within our institution. Accordingly, all analyses are descriptive and should not be generalised beyond this cohort.

Table 1. Demographic characteristics of STEM undergraduate participants (N = 297).

Characteristic	Category	Number	Percentage
Programme	Electronic and Electrical Engineering (EEE)	119	40%
	Computer Science (CS)	65	22%
	Civil Engineering with Transport (CET)	38	13%
	Materials Science and Engineering (MSE)	36	12%
	Mechanical Engineering (ME)	39	13%
Year/Level	First Year (Level 0)	157	53%
	Second Year (Level 1)	48	16%
	Third Year (Level 2)	89	30%
	Fourth Year (Level 3)	3	1%
Gender	Male	238	80%
	Female	59	20%

3.3. Survey Instrument Development and Validation

The survey combined established technology-adoption constructs with context-specific items relevant to educational chatbots. Core items were adapted from TAM/UTAUT domains (perceived usefulness, ease of use/effort expectancy, social influence, facilitating conditions). We added AI-relevant facets (e.g., language/terminology support, content alignment/accuracy, integrity/privacy) guided by the recent literature and the local teaching context. Content validity was supported through expert review (three reviewers in educational technology/STEM pedagogy) and a small pilot (n = 10) to refine wording and remove redundancies.

The final instrument comprised 28 items covering background characteristics, familiarity/comfort with AI, perceived usefulness, willingness to use, perceived benefits/concerns, desired features, and two open-ended prompts. Multi-item descriptive composites (e.g., perceived usefulness) showed acceptable internal consistency (Cronbach's $\alpha \approx 0.75$–0.85) and are used only for within-cohort description; we make no confirmatory measurement claims. The full item wording and anchors are provided in Appendix E.

3.4. Data Collection Procedure

Ethical approval was granted by the University of Leeds Research Ethics Committee (Ref. 2714; 8 March 2025). The survey was delivered online via secure links disseminated by course instructors over four weeks in Spring 2025. Participants received an information sheet, gave electronic informed consent, and completed the survey in ~10–15 min. No personal identifiers were collected; only complete responses were retained. Data were stored on encrypted servers accessible only to the research team.

3.5. Data Analysis

Analyses proceeded in three steps: (i) descriptive statistics and Spearman correlations among within-cohort acceptance variables; (ii) an exploratory factor analysis (EFA) attempt on binary concern indicators using an appropriate pipeline; and (iii) inductive thematic analysis of open-ended responses. We report item-level descriptives as the primary results. Factor and clustering attempts did not yield stable structures meeting the inclusion criteria and are therefore not presented as findings.

3.5.1. Quantitative Analysis

- We report item-level frequencies with 95% Wilson confidence intervals for proportions. We attempted an exploratory factor analysis with tetrachoric correlations, oblique rotation (e.g., oblimin), and parallel analysis for factor retention. This analysis did not reveal a stable or meaningful latent structure (parallel analysis suggested an essentially unidimensional structure with low explained variance), so we interpret concerns at the item level only and do not name factors.
- For acceptance variables, we computed Spearman rank correlations among three global measures—AI familiarity, comfort using chatbots, and willingness to adopt—and report these as exploratory within-cohort observations without causal interpretation.

3.5.2. Cluster Analysis

We explored whether responses exhibited any natural groupings by running k-means clustering on z-scored indices. Using Euclidean distance, all solutions showed very low separation; the best average silhouette was $\approx$0.21 at k = 3, indicating a weak tendency toward clustering. Under our a priori inclusion gate (average silhouette $\geq$ 0.25), these results did not qualify as a defensible segmentation. Accordingly, we do not report personas or any persona-based analyses.

3.5.3. Qualitative Analysis

Two researchers independently coded the open-ended responses using inductive thematic analysis. Discrepancies were reconciled through discussion and iterative refinement of the codebook. Themes were identified based on recurring patterns in student responses, with illustrative quotes selected for each theme. Counts are reported for transparency only and not for inference.

Transparency notes: for completeness, Appendix B now contains a brief statement that clustering was attempted but not retained due to poor separation; no centres, sizes, or profiles are reported.

Future work: If segmentation is of interest, future studies should (i) design for cluster ability with balanced, multi-site samples; (ii) use distance measures suited to mixed data (e.g., Gower) with partitioning around medoids (PAM) or model-based clustering; and (iii) assess stability (e.g., bootstrap/Jaccard) and external validity before advancing any personas.

3.5.4. Analytical Integration

Integration occurred at the interpretive stage, relating item-level descriptive patterns to inductive qualitative themes to contextualise student perceptions; no latent structures or personas were advanced.

4. Results

Scope notes for the results: All analyses below are descriptive and cohort-specific from a single-site convenience sample (N = 297; 53% first year; ~80% male). We report item-level frequencies with 95% CIs and a small set of within-cohort correlations. We do not perform between-group inference, confirm latent factor structures, or report personas/segments.

4.1. Respondent Demographics

Figure 1 shows the distribution of respondents by programme and year of study. Electronic and Electrical Engineering (EEE) constituted 40% of the sample; Computer Science constituted 22%; Civil Engineering with Transport constituted 13%; Materials Science and Engineering constituted 12%; and Mechanical Engineering constituted 13%. First-year students comprised 53% of the cohort; while second-year, third-year, and fourth-year students accounted for 16%, 30%, and 1%, respectively.

Figure 1. Distribution of survey respondents by (**a**) programme and (**b**) year of study.

For transparency, raw discipline-level descriptives appear in Appendix D; no inferential testing was conducted.

4.2. Familiarity, Attitudes, and Adoption Readiness

Most students reported being "familiar" or "very familiar" with AI (67%; 95% CI: 61.3–72.4; Figure 2a), and a large majority rated AI's future role in STEM education as "important" or "very important" (87%; 95% CI: 82.8–90.4; Figure 2b). This baseline familiarity translated into high adoption readiness: 78% expressed willingness to use AI chatbots ("somewhat/very likely"; 95% CI: 73.1–82.4; Figure 3a), with 79% reporting comfort using them ("somewhat/very comfortable"; 95% CI: 74.2–83.3; Figure 3b). Only 2% reported discomfort.

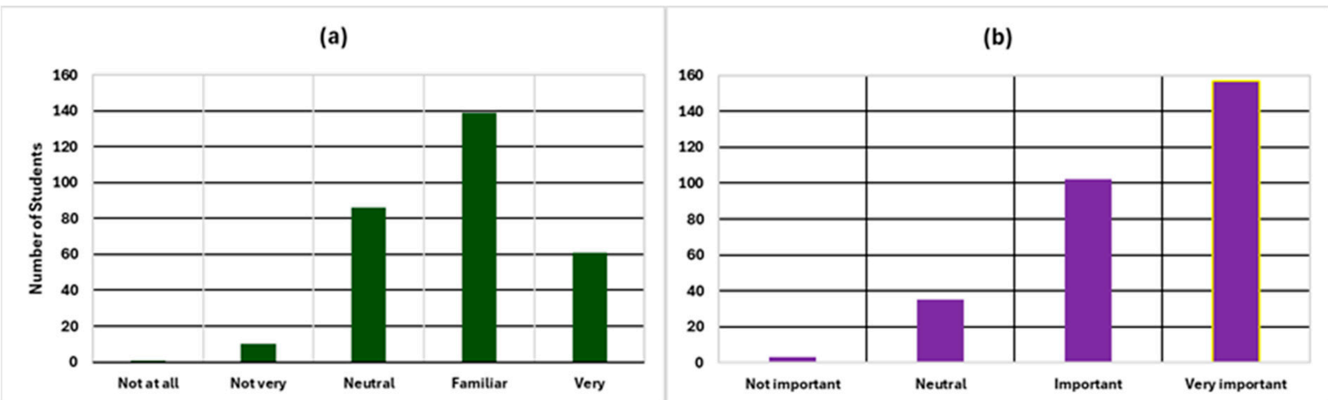

Figure 2. (**a**) Self-rated familiarity with AI and (**b**) perceived importance of AI in STEM education.

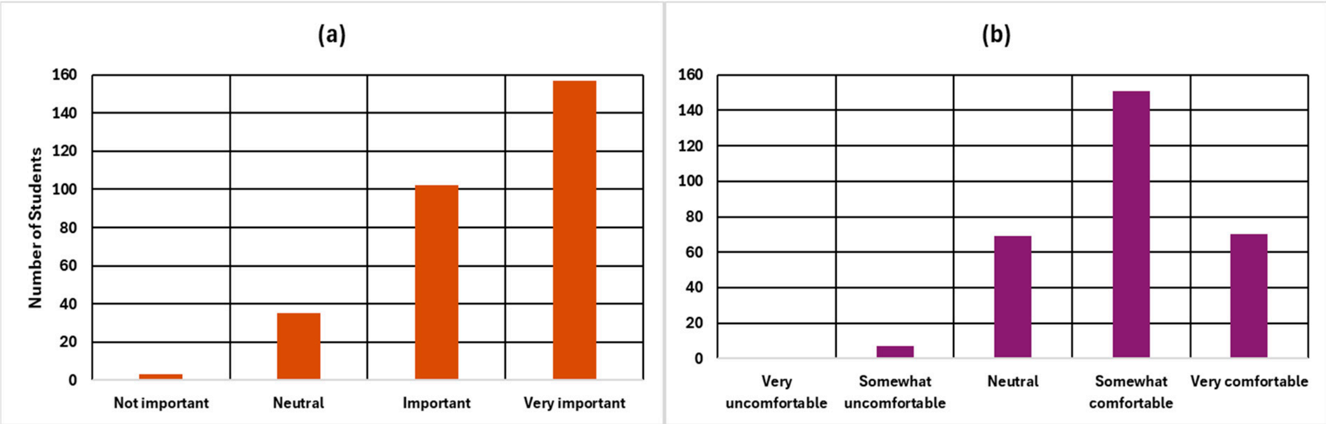

Figure 3. (**a**) Willingness to use an AI chatbot for learning and (**b**) level of comfort in using an AI chatbot.

Exploratory within-cohort correlations showed expected positive associations between acceptance variables (Figure 4). Comfort with chatbots showed the strongest association with willingness to use (ρ = 0.50), followed by perceived usefulness with willingness (ρ = 0.45) and AI familiarity with willingness (ρ = 0.37). These uncorrected bivariate correlations are descriptive only.

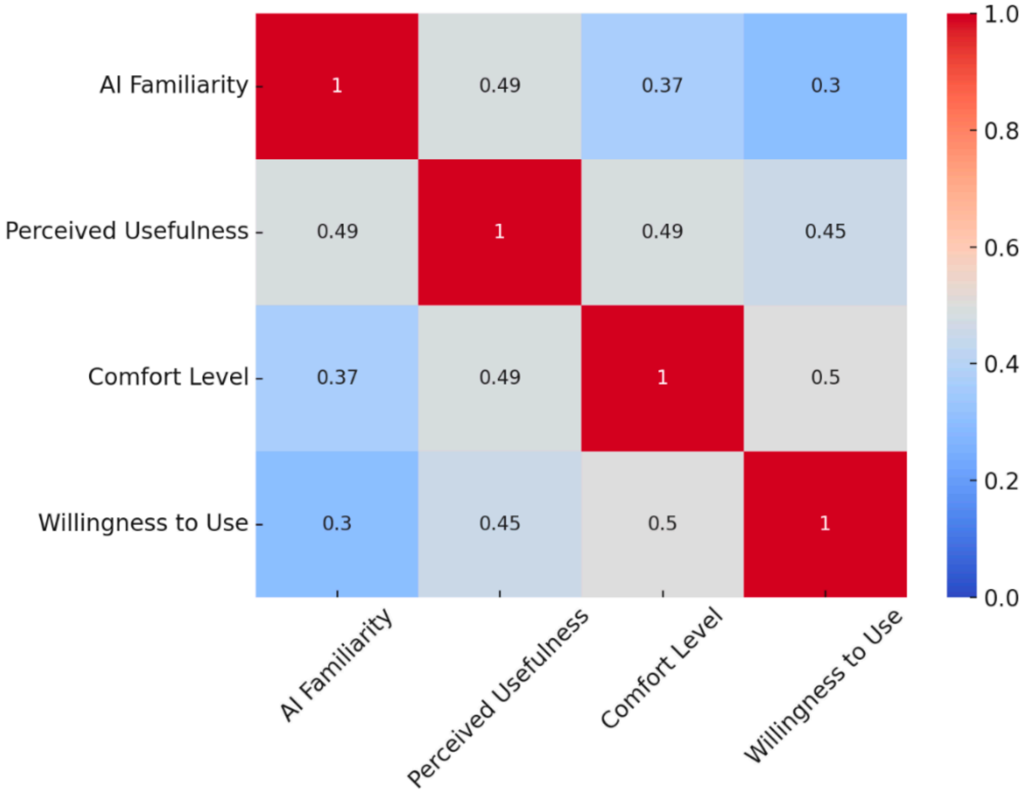

Figure 4. Correlation heatmap of key acceptance variables.

4.3. Perceived Educational Benefits

Students rated the extent to which AI chatbots could enhance learning across four domains on a five-point scale. Figure 5 summarises the average ratings (M ± SD) and the proportion selecting "very much"/"extremely."

- Overall learning: M = 3.87/5; 69% (95% CI: 63.4–74.2) "very much/extremely."
- Problem-solving: M = 3.47/5; 48% (95% CI: 42.3–53.8) "very much/extremely."

- Collaboration: M = 3.18/5; 35% (95% CI: 29.7–40.6) “very much/extremely.”
- Creativity: M = 3.16/5; 33% (95% CI: 27.8–38.5) “very much/extremely.”

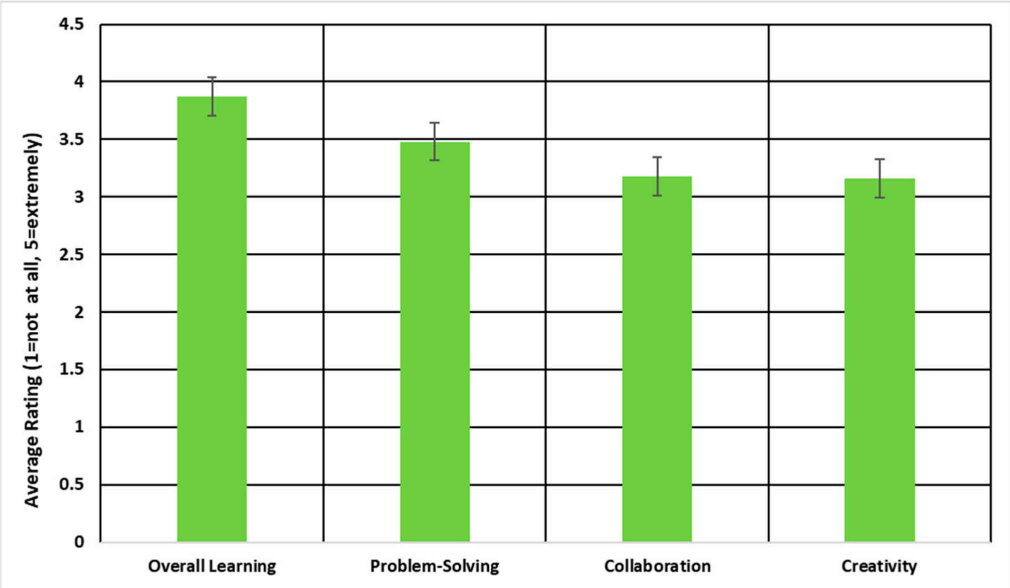

Figure 5. Average perceived enhancement (5-point scale; M ± SD) from AI chatbots across four learning domains (overall learning, problem-solving, collaboration, and creativity).

Taken together, students anticipated greater individual learning benefits (conceptual clarity and problem-solving) than gains in collaboration or creativity, with collaboration showing the widest dispersion. Within this cohort, the four domain items form a composite perceived learning enhancement index ($\alpha = 0.77$, descriptive use only); the scale mean (M = 3.42) is equal to the average of the four item means in Figure 5. The results are descriptive and cohort-specific.

In summary, students anticipated greater individual learning benefits than gains in collaboration or creativity, with expectations for collaboration showing the widest dispersion.

Note: The four domains in Figure 5 form a composite perceived learning-enhancement index ($\alpha = 0.77$; descriptive use only). The scale mean (M = 3.42) is equal to the average of the four item means in Figure 5 (see Appendix E, Table A3, for item wording and anchors).

Preview: Students’ high-level expectations (e.g., concept explanation, timely feedback, problem-solving support, anytime access) align with the feature requests summarised later (see Section 4.6). Detailed percentages are also reported in Section 4.6.

4.4. Concerns About AI Chatbot Use

Students expressed various concerns about using AI chatbots in STEM education (Figure 6). The most frequently endorsed concerns were as follows:

- Over-reliance/learning dependency: 67% (95% CI: 61.4–72.1).
- Content quality/accuracy issues: 52% (95% CI: 46.2–57.5).
- Reduced human interaction: 42% (95% CI: 36.5–47.8).
- Inability to ask follow-up questions: 25% (95% CI: 20.4–30.2).
- Language barriers in English: 5.1% (95% CI: 2.9–8.2).
- Fear of translation misunderstanding: 11.8% (95% CI: 8.4–15.9).

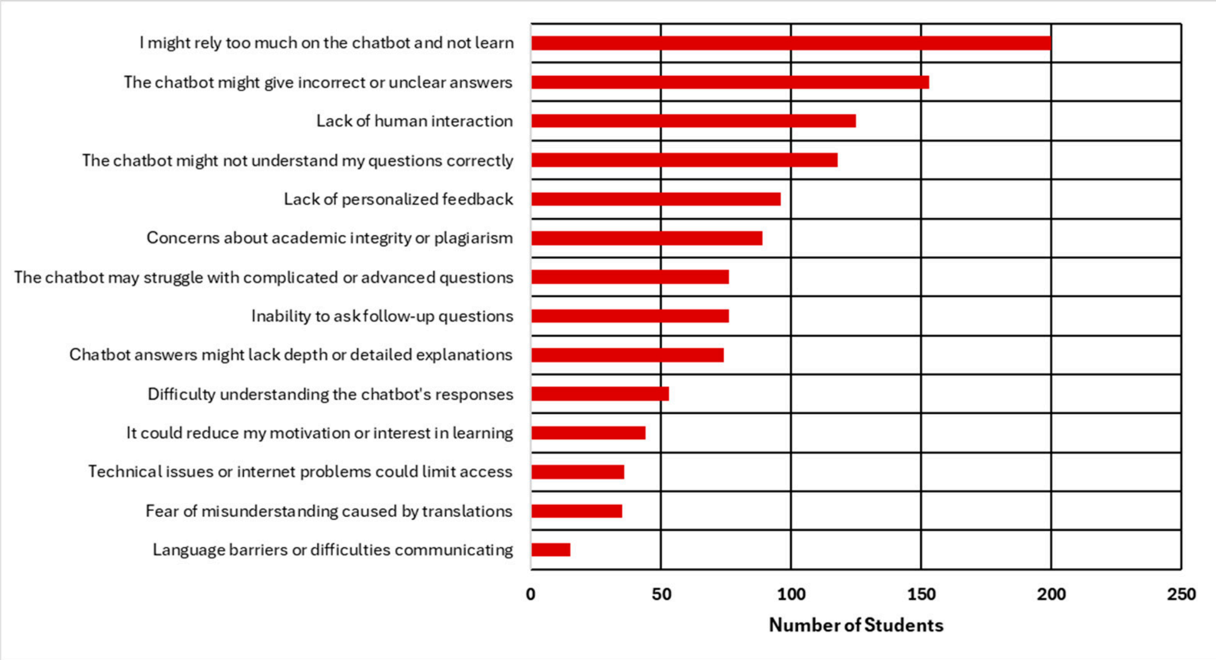

Figure 6. STEM students report the most common concerns about using AI chatbots for learning.

Combined, 16.8% (95% CI: 12.9–21.5) reported language-related concerns, which is distinct from the 52% who requested language support features (Section 4.6). These item-level frequencies inform implementation considerations without assuming a latent structure. Several students also raised privacy/data-handling concerns in open-ended comments; representative quotes are shown in Appendix C.

4.5. Language Barriers vs. Language Support Requests

Critical distinction: Only 16.8% (95% CI: 12.9–21.5) of students reported language-related concerns, with 5.1% indicating "language barriers or difficulties communicating clearly in English" and 11.8% citing "fear of misunderstanding caused by translations" (Figure 6). In contrast, 52% (95% CI: 46.3–57.7) requested language/terminology support features (e.g., glossaries, plain-language explanations; see Section 4.6).

Interpretation: Desire for clarity tools should not be conflated with experiencing a barrier. Many students may proactively seek terminology scaffolds to increase precision and confidence with technical vocabulary, even when their English proficiency is adequate.

Implications for design: Optional language scaffolds—inline glossary links, a plain-language toggle, bilingual exemplars, and terminology highlights—should be provided so students who need support can obtain it without imposing changes on those who prefer standard phrasing. Future pilots should evaluate the uptake and learning benefits of these features.

Limitations: We did not measure English proficiency levels or prior EMI experience; therefore, we cannot determine whether language concerns or support requests varied by proficiency—an essential question for future EMI research.

4.6. Requested Features

Figure 7 shows the distribution of requested features. The most frequently selected were the following:

- Help with technical terms/language: 52% (95% CI: 46.3–57.7).
- Ability to ask follow-up questions: 49% (95% CI: 43.3–54.8).
- Personalised responses: 43% (95% CI: 37.4–48.8).

- Step-by-step problem guides: 36% (95% CI: 30.7–41.6).

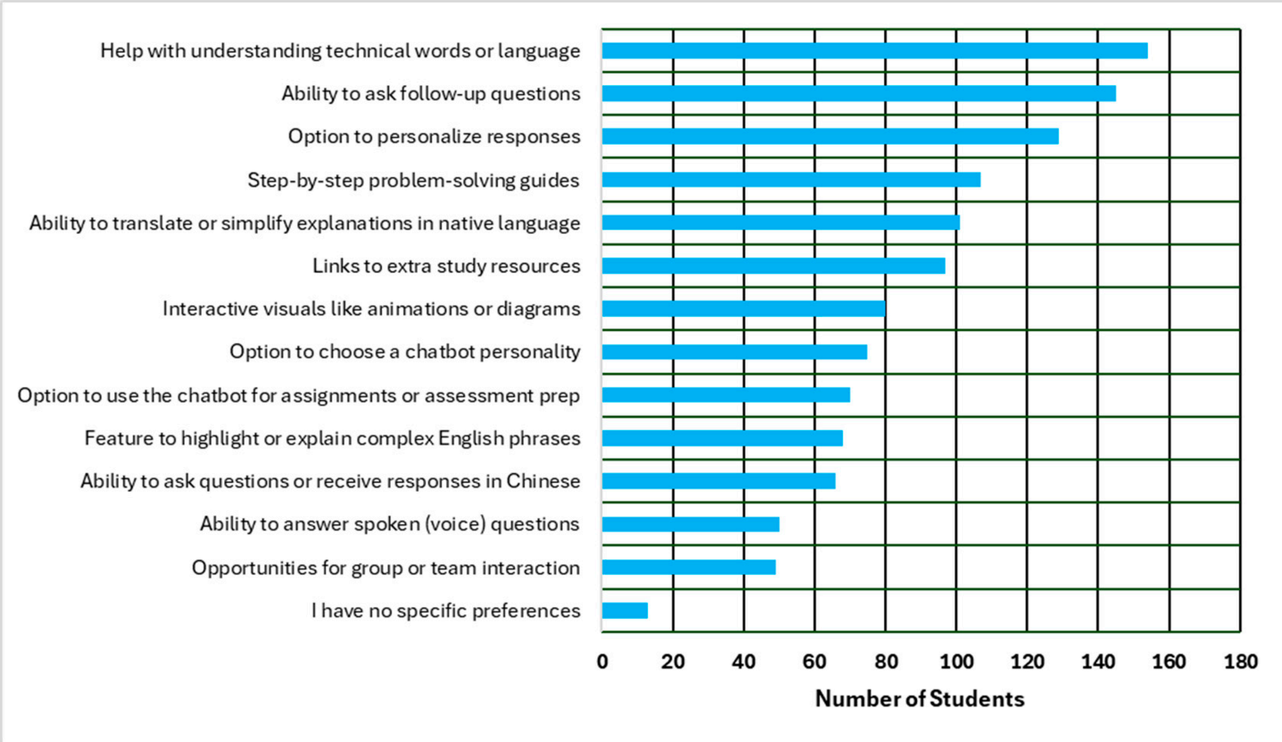

Figure 7. Desired features and functions in an AI learning chatbot by number of STEM students.

These preferences align with the cohort's most frequent concerns (Section 4.4) and the EMI context's emphasis on accessible terminology.

Other (lower-frequency) requests included choosing a chatbot "persona"/tone (~25%), voice-based Q&A (~23%), and group-work support (~16%); these are reported for transparency and are not used for inferential claims (see Figure 7).

Interpretive note: Interest in language/terminology support (52%) should be distinguished from reported language-related concerns (16.8%); many students appear to want proactive clarity tools even if they do not experience language barriers (see Section 4.4). We did not measure English proficiency, so we cannot test whether support requests vary by proficiency—an essential question for future EMI research.

4.7. Qualitative Themes

Two researchers independently coded open-ended responses using inductive thematic analysis. Discrepancies were reconciled through discussion and iterative refinement of the codebook. Analysis revealed multiple themes, with four major patterns emerging:

Theme 1: Efficiency
"AI chatbots could save me hours I currently spend searching for answers." (First-year, EEE)
Several students emphasised the time-saving potential for concept clarification and practice.
Theme 2: Verification Concerns
"I'd use it for initial guidance but would verify critical calculations myself." (Second-year, CET)
Interest was paired with appropriate scepticism about accuracy.
Theme 3: Integration Uncertainty
"I'm curious but not sure how it would fit into my studying." (First-year, ME)
Some students were unsure how to incorporate chatbots into existing study routines.
Theme 4: Language Support Needs (distinct from barriers)
"A glossary would help with technical terms even though I understand English fine."

(Second-year, CS)
Some students requested help with terminology despite not reporting language difficulties.

Additional themes include privacy concerns, fear of over-reliance, and a desire for follow-up capabilities.

Note. Themes from a single cohort (non-generalisable). See Appendix C for the complete codebook with all identified themes, definitions, and additional exemplar quotes.

5. Discussion

5.1. Summary of Findings

First and foremost, these findings are strictly context-bound and not generalisable beyond this cohort. We refrain from broad disciplinary conclusions, do not create student "personas," and do not impose any confirmatory latent constructs. Instead, we highlight the most frequently endorsed concerns and supports as pilot insights that warrant prospective evaluation in other settings.

Within this single cohort, willingness to adopt was high (78%), alongside salient item-level concerns about over-reliance/learning dependency (67%), content quality/accuracy (52%), and reduced human interaction (42%). We also distinguish actual language barriers (16.8% combined across two items) from interest in language/terminology support features (52%). The latter indicates that even students who do not report barriers may still value clarity tools (e.g., glossaries, plain-language explanations) for navigating technical terminology.

Methodological transparency: We attempted exploratory factor analysis and clustering, but neither yielded structures meeting inclusion criteria (parallel analysis indicated an essentially unidimensional concern structure; average silhouette for k-means = 0.21 < 0.25). We therefore report item-level descriptive patterns only.

Contextual factors: Patterns reflect a single English-medium Sino–UK programme with convenience sampling (53% first-year students; ~80% male), which limits representativeness even within the institution. This local context may shape high willingness and specific concerns and should not be inferred to broader STEM populations.

Cross-method consistency: Quantitative and qualitative evidence independently surface language-support needs: several students explicitly asked for terminology help, "even though I understand English fine" (Section 4.7). This reinforces our analytic distinction between barriers and supports. While not directly comparable, faculty evidence from Serbia similarly shows user/non-user differences alongside weak institutional support—patterns that resonate with, though do not confirm, this cohort's concerns (Popović Šević et al., 2025).

5.2. Questions for Future Research

The item-level patterns in this cohort raise three questions that warrant investigation through controlled studies:

1. Given that 67% of this cohort expressed over-reliance concerns and 52% worried about accuracy, would verification routines (e.g., source indicators, confidence ratings) and effort-preserving scaffolds reduce these concerns while maintaining learning benefits?
2. With 52% requesting language support features despite only 16.8% reporting barriers, would toggleable terminology glossaries and plain-language modes benefit EMI students broadly, or only those with lower English proficiency?
3. As 42% expressed concern about reduced human interaction, how do instructor-mediated versus independent chatbot activities affect both learning outcomes and student–instructor relationships?

Note: These considerations arise from one convenience sample and require prospective evaluation through controlled classroom studies. Future work should measure English proficiency to test differential benefits.

Reports from faculty in other settings note similar gaps in institutional support and training, reinforcing the need to pilot and evaluate these considerations locally (Popović Šević et al., 2025).

5.3. Discipline Patterns

We did not conduct or interpret between-discipline comparisons due to uneven subgroup sizes and the single-programme scope. Raw descriptives appear in Appendix D for transparency only; no inferential testing was performed.

6. Conclusions

This study documented how 297 STEM undergraduates at a single Sino–UK joint institution perceive AI chatbots for learning. The findings are strictly descriptive of this cohort and cannot be generalised. Students reported high willingness to adopt chatbots (≈78%) alongside specific concerns, most notably over-reliance/learning dependency (≈67%), content quality/accuracy (≈52%), and reduced human interaction (≈42%). A critical distinction emerged between those experiencing language-related barriers (≈16.8% combined) and those desiring language/terminology support features (≈52%): many students appear to want clarity tools proactively rather than as a solution for difficulty.

We attempted exploratory factor analysis and clustering using appropriate diagnostics; neither yielded stable structures meeting the inclusion criteria. Accordingly, the results are presented at the item level only, without latent factors or persona-based segmentation.

6.1. Summary of Contributions

- Cohort-level adoption profile. There is a high willingness and comfort to use chatbots in courses, coupled with clear concerns about learning dependency, accuracy, and diminished human interaction.
- Language support vs. barriers. Only a minority reported language barriers, yet a majority requested terminology/plain-language features—underscoring the value of optional clarity tools in English-medium contexts.
- Transparent limits and reporting. We explicitly confine inference to this single-site convenience sample and report item-level patterns with confidence intervals.

6.2. Research Questions Arising from This Descriptive Baseline

The item-level patterns documented in this cohort generate testable hypotheses for future controlled studies:

1. Verification and scaffolding effects: With 67% expressing dependency concerns and 52% questioning accuracy, would structure verification routines (e.g., source disclosure, confidence indicators) and effort-preserving scaffolds (e.g., progressive hints rather than direct answers) mitigate these concerns while preserving learning gains? How do different scaffolding approaches affect the dependency–learning outcome relationship?
2. Language support utility across proficiency levels: The distinction between students reporting language barriers (16.8%) versus those requesting terminology support (52%) raises an empirical question: Do optional language supports (e.g., toggleable glossaries, plain-language modes) benefit all EMI students equally, or primarily those below a certain English proficiency threshold? Would uptake patterns differ between voluntary clarity tools versus mandated simplification?
3. Human presence moderation effects: Given that 42% expressed concern about reduced instructor interaction, how does the integration model (instructor-mediated vs. independent vs. hybrid chatbot use) moderate both learning outcomes and student–

instructor relationship quality? What is the optimal balance between AI efficiency and human connection in STEM education?

These questions require multi-site experimental or quasi-experimental designs with adequate power to detect meaningful differences—methodological standards this descriptive baseline was not designed to meet.

6.3. Scope and Limitations

Interpretation should reflect the study's design constraints: a single-site convenience sample (53% first year, ~80% male, 1% seniors), cross-sectional self-reported data, and uneven subgroup Ns that preclude reliable comparisons. Our exploratory factor analysis (tetrachoric + oblique + parallel analysis) and clustering (silhouette ≈ 0.21) did not meet inclusion criteria; therefore, we refrain from factor- or persona-based claims.

6.4. Priorities for Future Research

Future studies should (i) incorporate direct measures of English proficiency to test whether language supports yield differential benefits; (ii) use multi-site sampling to assess generalisability; (iii) link perceptions to behavioural usage and learning outcomes; (iv) apply adequately powered measurement modelling (e.g., tetrachoric EFA/CFA with replication) where appropriate only after verifying data adequacy; and (v) examine whether the patterns observed here extend to other stakeholders (e.g., faculty) and contexts, particularly with respect to institutional support mechanisms (Popović Šević et al., 2025).

If future, appropriately sampled multi-site data allow, segmentation methods (e.g., model-based clustering/latent classes) can be explored with cross-validation.

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Appendix A. Attempted Exploratory Factor Analysis

Exploratory factor analysis was attempted using appropriate methods (tetrachoric correlations for binary items, oblique rotation, and parallel analysis for factor retention). The study did not yield a stable or interpretable latent structure meeting the inclusion criteria. Item-level frequencies are reported in the main text.

Appendix B. Attempted Clustering Analysis

K-means clustering was explored (k = 2–6). All solutions showed poor separation (average silhouette ≤ 0.21), below the 0.25 threshold for adequate clustering. No meaningful segments could be identified. Item-level descriptive statistics are reported in the main text.

Appendix C. Qualitative Codebook

Table A1. Qualitative codebook: Themes, definitions, and exemplar student quotes.

Theme	Definition	Example Quote (Student's Words)
Efficiency	Using AI to save time and obtain instant answers during study	"AI chatbots could save me hours I currently spend searching for answers in long textbooks." (First-year student, EEE). "It saved me time and helped me find answers instantly." (Second-year student, CS)
Verification Concerns/Accuracy	Concern that AI answers may be incorrect, shallow, or unreliable	"I'd use it for initial guidance but would verify critical calculations myself." (Second-year student, CET). "Sometimes, the answers aren't accurate or deep enough." (Third-year student, EEE)
Fear of Over-Reliance	Concern about becoming too dependent on AI and losing independent learning skills	"I'm worried that I might become too dependent on AI and stop thinking critically." (Third-year student, MSE). "I worry about becoming lazy and not learning properly." (First-year student, ME)
Integration Uncertainty	Uncertainty about how to incorporate chatbots into existing study routines	"I'm curious but not sure how it would fit into my studying." (First-year student, ME). "I don't know when it's appropriate to use AI for assignments." (Second-year student, CET)
Language Support Needs	Desire for tools to clarify technical terms and terminology (distinct from language barriers)	"A glossary would help with technical terms even though I understand English fine." (Second-year student, CS). "A built-in glossary would really help me follow the lectures." (First-year student, EEE)
Desire for Follow-Up Questions	Desire for AI to remember contexts and support multi-turn dialogue	"I'd like the AI to have memory so I can avoid tedious repeated questioning." (Second-year student, EEE). "It should allow back-and-forth conversation like a real tutor." (Third-year student, CS).
Privacy and Data Concerns	Concern about data storage, usage, and who can access student queries	"I'm concerned about who can see our questions and data." (First-year student, CS). "Will my questions be stored and used for grading?" (Second-year student, MSE)
Academic Support/Feedback	Using AI to clarify difficult concepts and provide study assistance	"AI helped clarify difficult concepts during revision." (Third-year student, CET). "It's useful for getting feedback on practice problems." (Second-year student, EEE)
Language Barriers	Actual difficulties communicating in English (distinct from terminology support)	"I worry I'll say something wrong in front of the class." (First-year student, MSE). "Sometimes I struggle to express my questions in English." (First-year student, CET)
Human Interaction Concerns	Concern about reduced contact with instructors and peers	"I don't want AI to replace discussions with my professor." (Second-year student, ME). "Learning with classmates is important for understanding." (Third-year student, EEE)

Note: Inductive thematic analysis with two coders and reconciliation; quotes anonymised by year/programme. Theme counts (if reported) are for transparency only and not used for inference, see Methods, Section 3.5.3.

Appendix D. Exploratory Descriptive Results by Discipline (For Transparency Only)

These exploratory descriptive statistics by discipline are provided for transparency. No significance testing was conducted, and these patterns should not be interpreted as confirmatory given the sample limitations (uneven group sizes: CS n = 65, CET n = 38, EEE n = 119, ME n = 39, MSE n = 36). The convenience sample and single-site nature preclude meaningful disciplinary comparisons.

Table A2. Perceived chatbot benefits by discipline (M ± SD; 5-point scale).

Discipline	Perceived Learning Enhancement (Mean ± SD)	Problem-Solving (Mean ± SD)	Collaboration (Mean ± SD)	Creativity (Mean ± SD)
Computer Science	4.00 ± 0.70	3.53 ± 0.83	3.11 ± 0.90	3.11 ± 0.98
Civil Engineering with Transport	3.98 ± 0.95	3.58 ± 0.90	3.48 ± 1.15	3.33 ± 1.12
Electronic and Electrical Engineering	3.87 ± 0.76	3.53 ± 0.96	3.20 ± 1.05	3.26 ± 1.01
Mechanical Engineering	3.83 ± 0.77	3.31 ± 0.67	3.03 ± 0.84	2.92 ± 0.81
Materials Science and Engineering	3.53 ± 0.65	3.31 ± 0.67	3.08 ± 0.87	3.00 ± 0.79

Appendix E. Survey Items and Response Anchors (Transparency Only)

Note: Items are used descriptively within this cohort; no confirmatory measurement claims are made. Response anchors reflect the administered survey.

Table A3. Perceived learning-enhancement items (5-point Likert).

Item Code	Item Wording	Anchors
PLE1	"An AI chatbot could enhance my overall learning in this course."	1 = Not at all . . . 5 = Extremely
PLE2	"An AI chatbot could enhance my problem-solving."	1 = Not at all . . . 5 = Extremely
PLE3	"An AI chatbot could enhance my collaboration."	1 = Not at all . . . 5 = Extremely
PLE4	"An AI chatbot could enhance my creativity."	1 = Not at all . . . 5 = Extremely

Table A4. Acceptance items (5-point Likert).

Construct	Item Wording	Anchors
Familiarity	"How familiar are you with AI/AI chatbots?"	1 = Not at all familiar . . . 5 = Very familiar
Comfort	"How comfortable would you be using an AI chatbot for learning?"	1 = Very uncomfortable . . . 5 = Very comfortable
Willingness	"How likely are you to use an AI chatbot if available in a course?"	1 = Very unlikely . . . 5 = Very likely
Perceived usefulness (single item)	"Overall, an AI chatbot would be useful for my learning."	1 = Strongly disagree . . . 5 = Strongly agree

Table A5. Concern checklist (binary; select all that apply).

Code	Concern Label (Used in Results, Section 4.4)
C1	Over-reliance/learning dependency
C2	Content quality/accuracy issues
C3	Reduced human interaction
C4	Inability to ask follow-up questions
C5	Language barriers in English
C6	Fear of misunderstanding from translations
C7	Privacy/data-handling concerns

Table A6. Desired features (binary; select all that apply).

Code	Feature Label (Used in Results, Section 4.6)
F1	Help with technical terms/language (glossary, plain-language mode)
F2	Ability to ask follow-up questions (multi-turn dialogue)
F3	Personalised responses
F4	Step-by-step problem guides
F5	Optional: Voice-based Q&A
F6	Optional: Group-work support
F7	Optional: Choose chatbot tone/style

Table A7. Open-ended prompts.

Prompt Code	Wording
OE1	"Please tell us about the most helpful ways an AI chatbot could support your learning."
OE2	"Please tell us about your main concerns regarding classroom use of AI chatbots."

References

Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education*, *21*, 10. [CrossRef]

Abdaljaleel, M., Al-Hunaiyyan, A., Alkhateeb, M., Baroun, H., & Alsharekh, A. (2024). A multinational study on the factors influencing university students' attitudes and usage of ChatGPT. *Scientific Reports*, *14*, 1983. [CrossRef]

Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of empirical research on ChatGPT in education. *Discover Education*, *3*, 60. [CrossRef]

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*, 319–340. [CrossRef]

Deng, X., & Yu, Z. (2023). A meta-analysis and systematic review of the effect of chatbot technology use in sustainable education. *Sustainability*, *15*(4), 2940. [CrossRef]

Department for Education (DfE). (2025). *Generative AI in education. Guidance*. First published 29 March 2023; last updated 12 August 2025. Department for Education. Available online: https://www.gov.uk/government/publications/generative-artificial-intelligence-in-education (accessed on 25 September 2025).

El Fathi, T., Saad, A., Larhzil, H., Lamri, D., & Al Ibrahmi, E. M. (2025). Integrating generative AI into STEM education: Enhancing conceptual understanding, addressing misconceptions, and assessing student acceptance. *Disciplinary and Interdisciplinary Science Education Research*, *7*, 6. [CrossRef]

Ertmer, P. A., & Ottenbreit-Leftwich, A. T. (2010). Teacher technology change: How knowledge, confidence, beliefs, and culture intersect. *Journal of Research on Technology in Education*, *42*, 255–284. [CrossRef]

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational contexts: A systematic literature review. *British Journal of Educational Technology*, *50*, 2572–2593. [CrossRef]

Henderson, C., Beach, A., & Finkelstein, N. (2011). Facilitating change in undergraduate STEM instructional practices: An analytic literature review. *Journal of Research in Science Teaching*, *48*, 952–984. [CrossRef]

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations* (2nd ed.). Sage Publications.

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Centre for Curriculum Redesign.

Kuhail, M. A., Alturki, N., Alramlawi, S., & Alhejori, K. (2023). Interacting with educational chatbots: A systematic review. *Education and Information Technologies*, *28*, 973–1018. [CrossRef]

León, C., Lipuma, J., & Oviedo-Torres, X. (2025). Artificial intelligence in STEM education: A transdisciplinary framework for engagement and innovation. *Frontiers in Education*, *10*, 1619888. [CrossRef]

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, *108*, 1017–1054. [CrossRef]

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). *Artificial intelligence in education: Challenges and opportunities for sustainable development*. UNESCO.

Pérez, J. Q., Daradoumis, T., & Martínez-Puig, J. M. (2020). Rediscovering chatbots in education: A systematic literature review. *Computer Applications in Engineering Education*, *28*, 1549–1565. [CrossRef]

Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, *12*, 22. [CrossRef] [PubMed]

Popović Šević, N., Šević, A., Slijepčević, M., & Krstić, J. (2025). AI adoption in higher education: Exploring attitudes and perceived benefits between users and non-users. *Online Journal of Communication and Media Technologies*, *15*(4), e202528. [CrossRef]

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Schei, O. M., Møgelvang, A., & Ludvigsen, K. (2024). Perceptions and use of AI chatbots among students in higher education: A scoping review of empirical studies. *Education Sciences*, *14*(8), 922. [CrossRef]

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modelling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, *128*, 13–35. [CrossRef]

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, *21*, 46. [CrossRef]

Smutny, P., & Schreiberova, P. (2020). Chatbots for learning: A review of educational chatbots for the Facebook messenger. *Computers & Education*, *151*, 103862. [CrossRef]

Tondeur, J., van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. T. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development*, *65*, 555–575. [CrossRef]

UNESCO. (2023). *Guidance for generative AI in education and research*. United Nations Educational, Scientific and Cultural Organization. Available online: https://unesdoc.unesco.org/ark:/48223/pf0000386693 (accessed on 20 August 2025).

U.S. Department of Education, Office of Educational Technology. (2023). *Artificial intelligence and future of teaching and learning: Insights and recommendations*. U.S. Department of Education. Available online: https://www.ed.gov/media/document/ai-reportpdf-43861.pdf (accessed on 18 July 2025).

U.S. Department of Education, Office of Educational Technology. (2024). *Designing for education with artificial intelligence: An essential guide for developers*. U.S. Department of Education. Available online: https://files.eric.ed.gov/fulltext/ED661949.pdf (accessed on 18 July 2025).

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*, 425–478. [CrossRef]

von Garrel, J., & Mayer, J. (2023). Artificial intelligence in studies—Use of ChatGPT and AI-based tools among students in Germany. *Humanities and Social Sciences Communications*, *10*, 799. [CrossRef]

Winkler, R., & Söllner, M. (2018). Unleashing the potential of chatbots in education: A state-of-the-art analysis. *Academy of Management Proceedings*, *2018*, 15903. [CrossRef]

Wollny, S., Schneider, J., Schröder, J., & Kremer, C. (2021). Are we there yet? A systematic literature review on chatbots in education. *Frontiers in Artificial Intelligence*, *4*, 654924. [CrossRef] [PubMed]

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education*, *16*, 39. [CrossRef]