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Students’ engagement with generative AI in academic learning: A self-determination theory and epistemic network analysis study

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ABSTRACT

This qualitative case study examines undergraduate students' engagement with generative artificial intelligence (GenAI) in academic learning in an English-medium university setting. This study employs self-determination theory (SDT) as the primary interpretive framework, treating technology acceptance perceptions (e.g., usefulness and ease of use) as descriptive cues rather than explanatory constructs. Data from 23 semi-structured interviews were analyzed using reflexive thematic analysis, complemented by epistemic network analysis (ENA) to examine the structural relationships among themes in students' discourse, with automated coding validated against a manually coded subset. Students frequently described GenAI as supporting efficiency and conceptual understanding; however, their accounts revealed persistent tensions concerning creativity, trust, and academic integrity. The ENA results showed that these concerns were systematically interconnected: discussions of learning support consistently co-occurred with verification practices, reflecting a “trust-but-verify” repertoire through which students calibrated their reliance on AI while maintaining epistemic control. Beyond instrumental evaluations, students' narratives highlighted broader value- and norm-related considerations, including algorithmic bias, environmental sustainability, and the positioning of AI within human–teacher learning networks. Overall, the findings suggest that students' engagement with GenAI is best understood as a motivated and socially situated learning practice shaped by the negotiation of competence, autonomy, and relatedness. Pedagogically, the results support a shift from prohibition-oriented responses to transparent institutional guidance, autonomy-supportive scaffolding of verification practices and AI literacy, and process-oriented assessment designs that make students' reasoning visible. Learning analytics approaches, such as ENA, may further assist educators in examining how these practices become integrated into students’ learning processes.

1. Introduction

Artificial intelligence (AI) offers unique opportunities for personalized learning, increased efficiency, and broader access to knowledge. These intelligent technologies are rapidly transforming higher education and reshaping traditional teaching and learning practices (Kasneci et al., 2023; Zhai, 2023). Moreover, as Bozkurt et al. (2023) observed, AI presents an opportunity to redefine the roles of human educators and AI in the educational sphere.

Integrating AI into educational environments offers numerous advantages; however, it also presents significant challenges, particularly concerning academic integrity, creativity, and the ethical application of AI in educational contexts (Miao & Holmes, 2023). For instance, in the absence of explicit institutional guidelines, students may use AI tools in ways that undermine critical thinking, originality, and ethical standards (Elkhatat et al., 2023). This lack of clarity can lead to inconsistent practices and uncertainty regarding acceptable AI use. It is essential to understand how students perceive AI's role in their learning and the strategies they employ to balance its benefits and risks, as this understanding is crucial for informing policy and pedagogy. Consequently, students frequently engage with AI tools without formal guidance, prompting inquiries into their practices, perceptions, and ethical awareness.

While the global discourse on artificial intelligence in education is

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rapidly advancing, empirical research on student experiences in Azerbaijan, particularly in the post-Soviet context, remains limited. Furthermore, although Azerbaijan's higher education system is undergoing gradual reforms (Isaeva et al., 2023), institutional policies regarding AI usage remain underdeveloped. Addressing this gap can elucidate how governance ambiguity and institutional transitions influence students' AI practices, norms, and self-regulation in academic learning. The importance of this gap is underscored by the fact that cultural, institutional, and policy contexts also shape how students integrate technologies into learning practices and how they interpret their pedagogical value (Venkatesh & Davis, 2000). Moreover, examining less explored environments enhances our understanding of AI integration in higher education settings.

To analyze students' engagement with GenAI, we used self-determination theory (SDT) as the primary interpretive lens because participants' accounts extended beyond instrumental evaluations to include agency, verification, and value-laden issues. Therefore, perceived usefulness and ease of use are reported as descriptive acceptance constructs rather than the main explanatory model.

This study advances existing research in three significant ways. First, it conceptualizes students' engagement with GenAI as a motivated and value-oriented learning practice shaped by autonomy, competence, and relatedness. Second, it integrates thematic analysis with epistemic network analysis (ENA) to offer an educational data analytics perspective on the co-occurrence of students' reasoning elements (e.g., the systematic linkage between utility discourse and verification discourse). Third, it provides evidence from a less commonly studied English-medium higher education setting, where institutional AI policies are still in the process of development. Furthermore, this study introduces an educational research approach that connects learners' discourse on GenAI with learning analytics modeling (ENA) and actionable pedagogical design principles. By combining qualitative interpretation with network-based educational data analytics, this study presents a replicable framework for examining the structure of human–AI learning practices and how they can be supported through instruction and policymaking.

Accordingly, this qualitative case study investigated the experiences of undergraduate students with GenAI in academic learning, focusing on how these tools influence study behaviors through the lens of SDT. Technology acceptance constructs were used as descriptive elicitation prompts. This study was guided by the following research questions:

RQ1. How do students conceptualize the influence of AI tools on their learning behaviors and study strategies?

RQ2. What ethical, emotional, and practical challenges do students encounter when using AI tools in learning?

2. Literature review

2.1. Motivation, agency, and values in students' GenAI engagement

Research on students' use of GenAI increasingly indicates that the primary concern extends beyond the mere adoption of the tool to encompass how learners integrate it into their educational processes while preserving agency, competence development, and ethical accountability. SDT offers a concise framework for analyzing these dynamics by positing that the quality of motivation and self-regulation depends on the degree to which learning environments fulfill three fundamental psychological needs: autonomy, competence, and relatedness (Deci & Ryan, 2000; Ryan & Deci, 2000). Within the context of SDT, students' descriptions of verification routines and trust calibration can be understood as endeavors to safeguard competence (ensuring accuracy and educational value) and autonomy (retaining ownership of academic work rather than delegating cognitive tasks). Concerns regarding over-reliance similarly correspond with SDT's differentiation between autonomous and controlled forms of engagement, underscoring the pedagogical significance of creating learning conditions that promote reflective choice rather than prohibition or unstructured permissiveness (Deci & Ryan, 2000; Ryan & Deci, 2000).

2.2. Situating technology-acceptance constructs

We recognize that perceived usefulness and perceived ease of use continue to serve as significant descriptors of students' initial evaluations of new technologies (Davis, 1989). Nevertheless, the available literature has highlighted that the technology acceptance model 's (TAM) limited construct may be overly restrictive when researchers seek to examine complex sociotechnical practices that include norms, identity, ethics, and contextual constraints (Bagozzi, 2007; Legris et al., 2003). Consequently, this study considers acceptance constructs as bounded descriptors situated within a broader SDT-informed framework of motivated, value-inflected engagement with generative AI in academic environments.

2.3. Implication for the analytic focus of this study

Building on SDT, our analysis focuses on how students articulate (a) tensions related to autonomy, such as agency, dependency, and ownership; (b) practices associated with competence, including verification, learning value, and error management; and (c) positioning related to relatedness and norms, including peer and institutional expectations and integrity, while also reporting instrumental evaluations such as usefulness and ease of use.

Recent syntheses consistently indicate that students employ GenAI for productivity and learning support, including activities such as brainstorming, summarizing, drafting, and language assistance, while simultaneously expressing ongoing concerns regarding accuracy, over-reliance, privacy, and academic integrity (Bobula, 2024; Chan & Hu, 2023; Kasneci et al., 2023; Ocen et al., 2025; Zhai, 2023). Across various contexts, students' AI use is influenced by institutional guidance and AI literacy, with recurring governance issues arising between bottom-up student innovation and top-down regulation (Bedenlier et al., 2020; Eyring & Christensen, 2011). Cross-national and region-specific evidence generally aligns with these patterns and underscores the necessity of instructor capacity building and curriculum-level AI literacy support (Faisal, 2024; Ravšelj et al., 2025).

Research indicates that students' attitudes toward GenAI vary across contexts and learner demographics; however, these studies typically emphasize perceptions of usefulness, risks, or adoption patterns rather than the motivational dynamics shaping students' learning practices. This variability highlights the necessity of integration strategies that are both localized and sensitive to field-specific differences (Bozkurt, 2023; Karahan; Bilgili, 2025; Ma et al., 2024; Stöhr et al., 2024). Such differences also appear to be influenced by variations in prior technological exposure, academic norms, and perceived risks, emphasizing that AI-related practices should be understood in their specific contexts.

Additionally, recent empirical studies underscore the unreliability of AI text detection tools, which are prone to generating false positives and false negatives. This renders detection-only enforcement strategies fragile and pedagogically unsound (Elkhatat et al., 2023; Giray, 2024a; Weber-Wulff et al., 2023). Consequently, international and sector-specific guidance advocates a transition from forbiddance to transparent educational policy frameworks. These frameworks should clarify acceptable use, enhance AI literacy, and align integrity expectations with practical feasibility (Miao & Holmes, 2023).

Regarding assessing students' work, researchers urge a redesign of methods that foreground process and authenticity, thereby reducing incentives for non-transparent AI use. Proposed models include the implementation of staged drafts with feedback cycles, the incorporation of oral components where appropriate, reflective process accounts, and tasks that require students to critique or enhance AI-generated outputs (El Khoury, 2024; González-Calatayud et al., 2021; Khlaif et al., 2025).

These approaches are reinforced by the establishment of clearer normative boundaries that distinguish legitimate AI-supported learning activities (e.g., brainstorming, language support, coding, and prompting assistance) from ghostwriting or work misrepresentation (Elkhatat et al., 2023; Miao & Holmes, 2023).

2.4. Learning processes: Productivity gains and cognitive offloading

Empirical research suggests that GenAI can enhance productivity and support iterative writing and learning processes through dialogic feedback and rapid revision cycles (Bozkurt, 2023; Giray, 2023; Noy & Zhang, 2023; Polakova & Ivenz, 2024; Zhuang et al., 2025; Zou et al., 2025). Meanwhile, cognitive psychology cautions that excessive reliance on external tools may result in cognitive offloading, potentially reducing opportunities to engage memory and reasoning, unless learning activities incorporate deliberate practice and metacognitive monitoring (Risko & Gilbert, 2016). These findings highlight the need for pedagogical frameworks that balance efficiency with opportunities for creativity, reflection, and independent problem solving.

The potential advantages of large language models (LLMs) are limited by the persistent risk of hallucinations and misinformation, highlighting the need for verification frameworks and critical evaluation strategies in both educational and professional settings (Huang et al., 2025; Ji et al., 2023). For instance, research indicates that LLMs can generate fabricated yet seemingly credible references and scientific content, thereby posing ethical risks and undermining academic integrity (Giray et al., 2024). Furthermore, concerns have been raised regarding the uncritical reliance on AI-generated outputs and the subsequent dissemination of misinformation in scholarly communication (Giray, 2024b).

Digital literacy research emphasizes strategies such as lateral reading, which involves consulting external sources to verify information, as essential for addressing misinformation. This method has been shown to improve accuracy and efficiency compared to vertical reading (Wineburg & McGrew, 2017). While such monitoring and verification practices resemble processes described in self-regulated learning research, the present study does not operationalize SRL constructs and therefore references this literature only as contextual background. Additionally, the SIFT heuristic (Stop, Investigate the source, Find better coverage, Trace claims) provides a practical framework for evaluating credibility in AI-supported contexts (Caulfield, 2019). Incorporating these practices into academic curricula implements a “trust but verify” approach, thereby equipping students to critically engage with AI-generated outputs while minimizing the risks associated with content that is plausible yet incorrect (Giray et al., 2025; Ji et al., 2023; Huang et al., 2025).

Similarly, researchers have highlighted that the expansion of LLMs without deliberate data curation, value alignment, and transparent documentation poses significant risks, including an increase in systemic biases, obscuring data provenance, and reinforcing opacity in model behavior (Bender et al., 2021).

These sociotechnical risks extend beyond technical dimensions to encompass ethical concerns, intersecting with issues of fairness, accountability, and representational harm–issues that students have increasingly raised regarding the use of AI in education. Consequently, scholars and policy bodies have advocated governance frameworks that prioritize awareness, transparent reporting of model limitations, and human oversight in educational contexts. Such measures aim to ensure that AI integration supports equity and trustworthiness, rather than preserving hidden forms of discrimination or epistemic injustice.

Numerous studies have found that students frequently perceive GenAI as an integral component of a comprehensive learning ecosystem that includes teachers, peers, platforms, and material artifacts. This perspective is consistent with Actor–Network Theory (ANT), which examines how human and non-human agents collaboratively facilitate learning activities (Fenwick & Edwards, 2010). This conceptualization underscores that AI does not replace but rather interacts with existing pedagogical relationships and infrastructures. Meta-analytic evidence highlights the enduring importance of teacher–student relationships for engagement and achievement, suggesting a complementary division of labor: AI tools can enhance explanations, practice, and feedback, whereas instructors provide motivation, judgment, and care, dimensions that remain distinctly human and relational (Roorda et al., 2011). This ecological perspective positions AI as a mediating resource rather than a replacement, emphasizing the necessity of design strategies that integrate technological affordances with the social and emotional dimensions of learning.

Although a rapidly expanding body of research addresses the benefits, risks, and governance challenges associated with generative AI in education, comparatively little work examines how students integrate these technologies into their learning practices from a motivational perspective. In particular, existing studies rarely analyze how concerns related to agency, competence development, and normative expectations interact within students' reasoning about AI use. To address this gap, the present study employs SDT as its primary interpretive framework and integrates reflexive thematic analysis with ENA to examine how competence, autonomy, and relatedness concerns co-occur in students' discourses about generative AI-supported learning (Shaffer et al., 2016).

3. Methodology

3.1. Research design

This qualitative case study employed semi-structured interviews to investigate undergraduate students' engagement with GenAI in academic learning and its relationship with study behaviors. Self-determination theory (Deci & Ryan, 2000; Ryan & Deci, 2000) was used as the primary interpretive framework, emphasizing how students' narratives reflected the satisfaction or frustration of their need for autonomy, competence, and relatedness. The interview prompts included perceived usefulness and perceived ease of use to capture participants' initial evaluations. Analytically, these constructs were categorized descriptively, while the interpretation concentrated on needs relevant to SDT, such as autonomy, competence, and relatedness, as well as emerging ethical and sociotechnological themes. Thus, usefulness and ease-of-use prompts were included solely to facilitate participants' recall of concrete AI-use episodes and not as constructs guiding interpretation.

3.2. Participants

This study was conducted at a research-intensive English-medium university in Azerbaijan that enrolls approximately 5000 students. As one of the pioneering institutions in the region to adopt Western-style, student-centered pedagogical approaches prior to the dissolution of the Soviet Union, it offers a unique context for examining emerging practices and norms in this area. At the time of data collection, there was no institutional policy regarding the use of GenAI, facilitating a naturalistic exploration of its utilization in this study.

Twenty-three undergraduate students, representing various majors and academic years, were recruited using maximum variation and snowball sampling techniques to ensure a wide range of perspectives. Participation was voluntary, and verbal consent was obtained from all participants. The eligibility criteria included current enrollment in an English-medium program and prior experience with at least one AI tool (e.g., ChatGPT). The gender distribution was balanced, comprising 12 males and 11 females. The majority of participants were in their first year ($n = 15$; 65.2%), with smaller cohorts in the second ($n = 4$; 17.4%) and third years ($n = 3$; 13.0%); one participant did not specify their year of study. The participants' academic disciplines were categorized into five clusters: Computing and Engineering ($n = 10$; 43.5%), Business and Management ($n = 5$; 21.7%), Education and Humanities ($n = 4$; 17.4%), Tourism and Hospitality (n = 2; 8.7%), and Social Sciences (n = 2; 8.7%). This distribution indicates a predominantly STEM-oriented sample, with representation from social sciences and professional fields.

The diversity of the participants' demographics, including gender, academic discipline, and year of study, enhanced the validity and transferability of the findings. The adoption of GenAI and its perceptions are influenced by disciplinary norms, digital literacy, and academic maturity. For instance, students in computing disciplines may perceive AI as a technical tool, whereas those in the humanities may regard it as a cognitive partner in the learning process. Additionally, gender and cultural diversity impact attitudes toward technology, trust, and ethical considerations, which are critical variables in AI in education research. By capturing a heterogeneous sample, this study mitigated bias, reflected real-world learning ecologies, and supported the development of inclusive policies and pedagogical strategies.

Table 1 summarizes the demographic characteristics of the participants, including their field of study, academic year, and gender, to facilitate the contextual interpretation of the study findings.

3.3. Procedures

Interviews were conducted in English via Microsoft Teams between July and August 2025, with each session lasting for 30–45 min. The sessions were audio-recorded, transcribed, and verified for accuracy. The interview protocol comprised 40 questions organized around topic domains that captured (a) technology-use descriptors (usefulness and ease of use), (b) affective orientations and trust, (c) ethical, policy, and environmental considerations, (d) verification practices, and (e) the positioning of AI within students' learning networks (e.g., teachers, peers, and other resources). Additionally, the protocol incorporated prompts that encouraged participants to recall specific episodes, such as assignments in which AI was beneficial or misleading.

3.4. SDT-informed analytic framework & RQ alignment

The analytical framework was meticulously structured to ensure a coherent transition from theoretical constructs to empirical assertions. Table 2 summarizes how the interview topic domains, including descriptors of usefulness and ease, facilitated the design of prompts, how responses were systematically coded into subthemes, and how these themes aligned with the research questions. The constructs of autonomy, competence, and relatedness from SDT were employed as sensitizing concepts during the interpretative process, while remaining receptive to inductive themes that extended beyond predefined categories.

Table 1
Demographics of participants.

Participant	Field of Study	Year	Gender
1	Computer Engineering	1st Year	Male
2	Humanities	2 nd Year	Female
3	Petroleum & Gas Engineering	1st Year	Female
4	Tourism Management	1st Year	Female
5	Computer Science	1st Year	Male
6	Computer Engineering	1st Year	Male
7	Translation	1st Year	Female
8	Computer Science	1st Year	Male
9	Marketing	1st Year	Female
10	Finance	1st Year	Female
11	Computer Science	1st Year	Male
12	Computer Science	1st Year	Male
13	English Language Teaching (ELT)	2 nd Year	Female
14	Finance	1st Year	Female
15	Computer Science	1st Year	Male
16	Management	1st Year	Female
17	International Relations	Not Spec.	Female
18	Political Science	3rd Year	Female
19	Chemistry Education	3rd Year	Male
20	Marketing	2 nd Year	Male
21	Tourism	2 nd Year	Male
22	Computer Science	1st Year	Male
23	Chemical Engineering	3rd Year	Male

3.5. Data analysis

The data were analyzed using a sequential qualitative–quantitative approach, commencing with a reflexive thematic analysis and subsequently employing ENA to model the co-occurrence structure of themes within the participants' interview discourse. Reflexive thematic analysis was used to discern patterned meanings across the dataset and to develop an interpretive account of participants' reasoning. Consistent with reflexive thematic analysis, the processes of coding and theme development were approached as theory-informed sense-making rather than as a reliability-driven procedure; thus, emphasis was placed on transparency, reflexivity, and evidential warrant rather than on inter-rater reliability metrics (Braun & Clarke, 2006, 2019, 2024). The analysis proceeded through iterative familiarization, initial coding, and theme development, integrating deductive sensitization from SDT (autonomy, competence, and relatedness) with inductive openness to themes that extended beyond the predefined categories (Braun & Clarke, 2006, 2019). Analytic memos were maintained throughout the study to document interpretive decisions and examine how the researcher's positioning may influence theme construction (Braun & Clarke, 2019; Nowell et al., 2017).

To clarify the analytical progression, when a participant remarked that they "*use AI to generate an explanation, but I always cross-check with other sources because it can be wrong,*" the segment was initially coded as instrumental support (usefulness), verification/triangulation, and error awareness. During the development of themes, these codes were consolidated under a broader theme encapsulating competence protection through verification and interpreted as part of a recurrent "trust-but-verify" repertoire. This procedure was systematically applied across the dataset by iteratively comparing coded segments, refining the code definitions, and consolidating themes when they captured coherent patterns supported by multiple data extracts (Braun & Clarke, 2006, 2019). Where counts are reported (e.g., n = number of participants referencing a theme at least once), they are provided descriptively to indicate prevalence within this case sample rather than as statistical evidence of generalizability (Braun & Clarke, 2019). Furthermore, the outputs of the ENA were visualized as interactive network plots, facilitating a comparison of the clustering of various reasoning elements. The positioning and thickness of the edges were interpreted as indicators of how students structurally integrated motivational, ethical, and instrumental considerations into their teaching. These visualizations were not regarded as statistical evidence but as analytical aids that enabled the identification of discourse patterns that aligned with SDT constructs and extended thematic insights. To ensure analytic transparency, themes were mapped to the research questions and theoretical claims via an Evidence Crosswalk (Appendix).

In light of documented concerns regarding "hallucinations" in large language models, verification was prioritized as the central analytical approach. The validation strategies employed by the participants were analyzed with reference to lateral reading methodologies, which emphasize cross-referencing among sources and the exercise of evaluative judgment (Caulfield, 2019; Wineburg & McGrew, 2017).

To integrate thematic interpretation with an educational data analytics perspective, we employed an ENA to investigate whether interpretive linkages among themes were reflected in systematic co-occurrence patterns. Learning analytics involves the analysis of learner-related data to advance the understanding and improve educational processes and environments (Ferguson, 2012; Siemens & Long, 2011). Within this field, ENA provides a method for modeling and visualizing the associative structure of qualitative discourse by quantifying the co-occurrence of codes within defined analytic windows, thereby facilitating the examination of learners' reasoning (Shaffer, 2017; Shaffer et al., 2016).

Table 2
Topic-domain–prompt–code–theme–RQ alignment.

SDT Need	Analytic Focus (Descriptors + Practices)	Example Interview Prompts	Representative Codes → Sub-themes	Theme	RQ(s)
Competence	Instrumental learning support and understanding	"Tell me about a time AI helped you understand a concept or complete a task."	Time-saving; concept clarification; skill practice	Learning Support (Efficiency & Time-saving; Conceptual Support; Skill Development)	RQ1
Competence	Verification and epistemic control	"How do you check whether AI output is correct?"	Lateral reading; cross-checking sources; citation requests	Trust & Verification (Verification Practices; Cross-checking)	RQ1–RQ2
Autonomy	Agency, dependency, and ownership of work	"Do you ever worry about relying too much on AI?"	Creativity concerns; dependency awareness; strategic use	Autonomy & Agency (Creativity vs. Dependency; Strategic Use)	RQ1–RQ2
Autonomy	Ease and accessibility shaping choice of tool use	"What makes AI easy or difficult to use in your studies?"	Accessibility; prompt literacy; subscription barriers	Access & Usability (Accessibility; Prompting & Personalization; Technical/Subscription Barriers)	RQ1–RQ2
Relatedness	Norms, institutional expectations, and integrity	"What do you consider fair or unfair when using AI?"	Boundary setting; policy ambiguity; academic integrity concerns	Ethical & Normative Context (Academic Integrity; Lack of Guidance; Privacy/Bias)	RQ2
Relatedness	Positioning AI among teachers and peers	"Where does AI fit among teachers, friends, and other resources?"	Teacher irreplaceability; AI as assistant; motivational support	Human–AI Learning Networks (Positioning; Human vs. AI Agency; Motivation/Companion)	RQ1
Values/ Responsibility *(cross-cutting)*	Societal and environmental awareness	"Do you have any concerns about the broader impacts of AI?"	Energy use awareness; sustainability concerns	Awareness of Impact (Environmental Awareness; Future of Teaching/Learning)	RQ2

In this analysis, the participants served as the unit of analysis, with each interview regarded as an independent conversation. The analytic subthemes functioned as network nodes. Transcripts were divided into stanzas at the paragraph level, and the codes were evaluated using a binary presence/absence logic within each stanza. A stanza-by-code matrix was subsequently employed to compute co-occurrence networks, where edges denote the weighted strength of code co-occurrence within stanzas (Shaffer et al., 2016). These networks were aggregated at the participant level and projected into a low-dimensional ENA space using a singular value decomposition.

To facilitate the large-scale operationalization of nodes, we implemented a dictionary-based automated coding methodology. Definitions from the codebook were converted into keyword patterns and regular expressions, allowing for a systematic application across the dataset. Given that dictionary-based coding can result in under- or over-triggering, depending on the linguistic context, we conducted a rigorous validation procedure using a manually coded subset of the data. Specifically, a stratified sample comprising 20% of the paragraph-level stanzas across transcripts was independently coded by the research team using the original codebook. These manual codes were then compared with the automated assignments generated by the dictionary-based procedure to assess their reliability.

We assessed the alignment between manual and automated coding through a descriptive comparison of matched and mismatched coding decisions, quantified using percent agreement and Cohen's kappa (κ). The comparison indicated a substantial level of agreement, with percent agreement at 86% and Cohen's kappa at $\kappa = 0.78$, consistent with acceptable levels reported in comparable mixed qualitative–computational coding approaches. Most discrepancies stemmed from contextual ambiguities, such as negation, implicit meaning, or metaphorical language, which occasionally led to false positives or missed codes. To address this, we iteratively reviewed these disagreements to refine our keyword patterns and minimize errors. This refinement process improved the correspondence between manual and automated coding while increasing transparency regarding the strengths and limitations of the automated procedure. Ultimately, we conceptualized the dictionary-based approach not as a replacement for qualitative interpretation but as a structured analytic tool that supported thematic modeling by capturing patterns of thematic co-occurrence within the ENA. These validation results provide reasonable confidence that the automated coding captured the intended thematic constructs while appropriately acknowledging the interpretive constraints inherent in dictionary-based techniques.

To assess whether the observed network structure surpassed chance expectations, we conducted a permutation test ($N = 500$) that maintained each code's overall frequency by shuffling code indicators within participants across stanzas. We interpret ENA outputs as indicative of structural associations in participants' discourse (co-occurrence patterns) rather than causal relationships (Shaffer et al., 2016). Although ENA is presented as exploratory owing to dictionary-based coding, it offers an explicit, replicable account of the relational structure underlying the qualitative findings and aids in identifying stable thematic linkages for future studies.

3.6. Trustworthiness

Trustworthiness was enhanced using various strategies. Credibility was supported by investigator triangulation, comprehensive descriptions with verbatim quotations, and negative case analysis. Dependability was ensured by maintaining a transparent coding trail, versioned analytic memos, and peer debriefing. Confirmability was strengthened through auditability provided by the appendices and traceable participant identifiers. Simultaneously, transferability was facilitated by detailed contextual accounts of the institutional setting and the diversity of the student body. Theme saturation was achieved by conducting 18–20 interviews, with subsequent cases elaborating on the established subthemes.

3.7. Researcher reflexivity

During the interviews, the research team maintained reflexive memos to document their assumptions, disciplinary perspectives, and power dynamics. Counterexamples (e.g., creativity loss, dependence, and resistance) were intentionally sought to mitigate confirmatory bias and contextualize the findings within Azerbaijan's cultural and institutional framework. Given the known risks of privacy breaches and hallucinations associated with AI, the interviews were designed to avoid prompting participants to disclose sensitive AI input.

3.8. Ethical considerations

This study adhered to institutional ethical standards. Informed consent was obtained from the participants, who were pseudonymized (P1–P23), and identifying details were removed from the transcripts and quotations. The interview questions were designed to avoid eliciting personal data entered into AI platforms, and safe-use practices were emphasized. This study was conducted in full compliance with the ethical principles outlined in the Declaration of Helsinki and was approved by the appropriate institutional review board prior to its initiation.

4. Findings

This section presents the findings from 23 semi-structured interviews exploring students' engagement with GenAI in academic settings. The participants discussed both the practical benefits and critical concerns surrounding AI utilization. Many students emphasized the efficiency and accessibility of AI tools, noting that these technologies streamline tasks and enhance the understanding of complex materials. At the same time, students frequently expressed concerns about academic integrity, the reliability of AI-generated information, and the potential impact of AI on creativity and independent thinking. Beyond these practical considerations, some participants contemplated broader ethical and societal implications, including issues related to privacy, environmental sustainability, and bias in AI training data. A few students described AI as a motivational companion or noted that exposure to AI tools influenced their academic paths. Collectively, these perspectives suggest that students view AI not merely as a technical tool but as an integral component of a broader sociotechnical learning ecosystem.

Table 3 provides a comprehensive summary of the themes and subthemes identified through the analysis, demonstrating their alignment with the psychological frameworks delineated in SDT, specifically autonomy, competence, and relatedness (Deci & Ryan, 2000; Ryan & Deci, 2000). This alignment clarifies the organization of the findings presented below.

Fig. 1 presents a visual depiction of the interconnections among the themes, illustrating the thematic map of students' engagement with AI.

In alignment with the theoretical framework of SDT, the findings are structured around the three core psychological needs posited by the theory: *competence*, *autonomy*, and *relatedness* (Deci & Ryan, 2000; Ryan & Deci, 2000). While students often highlighted the instrumental aspects of AI usage, such as efficiency and usability, these assessments were situated within broader discussions of learning effectiveness, personal agency, and social norms.

4.1. Competence: Learning support and verification practices

Participants frequently characterized GenAI as a valuable resource that facilitates their learning processes, particularly in comprehending complex material, refining academic skills, and managing time constraints. From the perspective of SDT, these narratives reflect experiences related to *perceived competence*, which pertains to students' sense of efficacy in engaging with academic tasks and learning environments (Deci & Ryan, 2000).

Among the participants, a majority (19 out of 23) identified GenAI as advantageous for improving efficiency and saving time, particularly in tasks such as text summarization, the generation of practice questions, and coding assistance. One student elaborated:

> “Artificial intelligence plays a crucial role … to save our time … [a text that would take] two or three minutes [with AI] … by myself, I would probably spend one hour” (P2).

Fifteen participants characterized AI as offering conceptual assistance by facilitating the simplification of complex readings or the generation of practice questions:

> “I uploaded some PDF files, and I asked it to make about 60 questions … it helped me understand [the] topic better” (P12).

Similarly, twelve students indicated that they utilized AI tools to enhance their academic competencies, including writing, programming, and the preparation of presentations:

Table 3
Themes, sub-themes, frequencies and SDT Alignment.

SDT Need	Theme	Sub-Themes	Frequencies (n = 23)
Competence	Learning Support	Efficiency & Time-saving	19
		Conceptual Support	15
		Skill Development	12
Competence	Trust & Verification	Verification Practices	15
		Cross-checking with Sources	9
Autonomy	Autonomy & Agency in AI Use	Creativity vs. Dependency	8
		Evolving Attitudes toward AI	9
Autonomy	Access & Usability	Accessibility	18
		Prompting & Personalization	13
		Technical/ Subscription Barriers	8
Relatedness	Ethical & Normative Context	Academic Integrity	16
		Lack of Institutional Guidance	12
		Privacy Concerns	7
		Bias in Training Data	3
Relatedness	Human–AI Learning Networks	Positioning AI among People and Tools	19
		Human vs. AI Agency	12
		AI as Motivator/ Companion	4
Values/ Responsibility (cross-cutting)	Awareness of Impact	Environmental Awareness	6
		Future of Teaching & Learning	11
Developmental Trajectories (interpretive extension)	Transformative Influence	Career Redirection	2
		Risks for Novice/ Younger Learners	3

> “I use ChatGPT mainly to understand difficult topics, getting help with writing essays, coding problems if I am stuck, [and] finding ideas for presentations” (P1).

Despite these advantages, students consistently emphasized the need to validate AI-generated outputs. Fifteen participants reported employing a “*trust-but-verify*” strategy in which AI responses were corroborated with course materials, textbooks, or alternative sources.

> “If I do not trust, I look at our PDF or [a] professional YouTube channel … I can check some information” (P1).

Nine participants reported using structured crosschecking practices, which included requesting citations or consulting multiple sources before accepting claims generated by AI.

> “First … check my own resource … then … official sites … [and] ask ChatGPT to give me source links” (P8).

The observed practices indicated that students endeavored to maintain epistemic control over their learning processes by employing verification routines to ensure the accuracy and reliability of information.

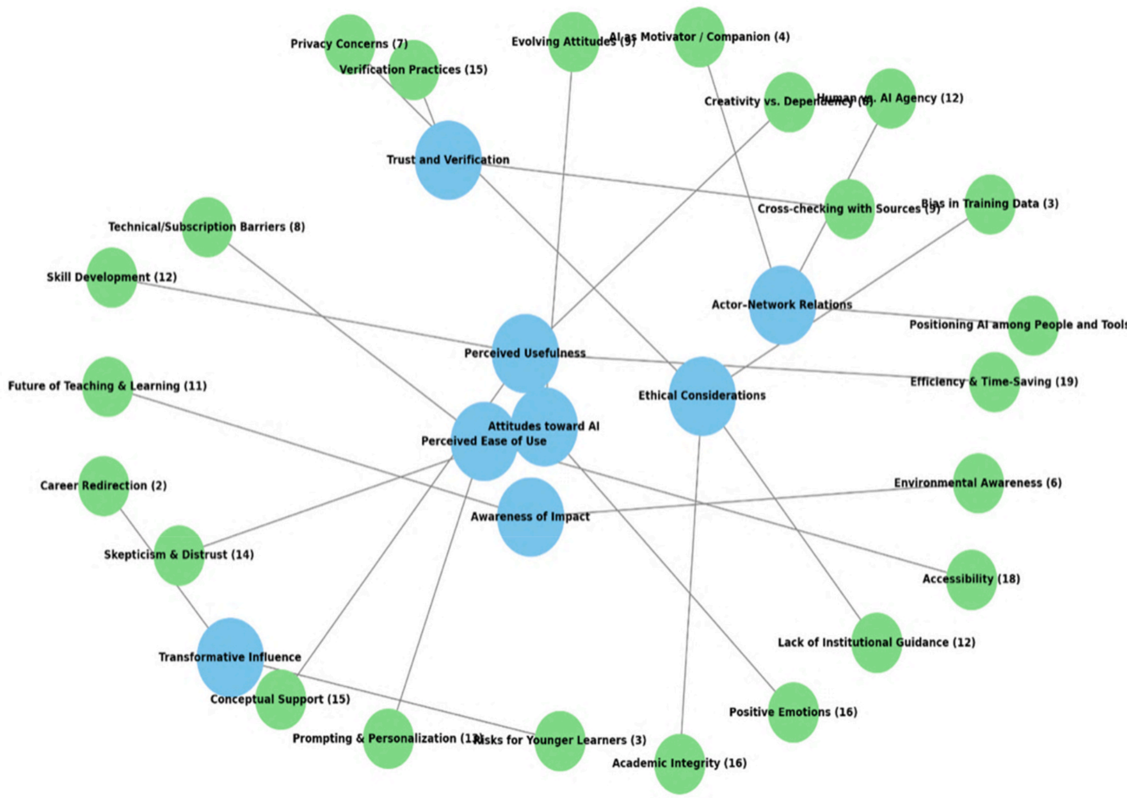

Fig. 1. Thematic map of students' engagement with AI.

4.2. *Autonomy: Agency, dependency, and strategic AI use*

The students' narratives also highlighted ongoing negotiations concerning autonomy in their interactions with AI tools. In SDT, autonomy refers to the experience of volition and psychological ownership of one's actions (Ryan & Deci, 2000). Participants frequently articulated the challenge of balancing the efficiency benefits provided by AI with the need to maintain independent thinking and creative engagement.

Eight participants expressed concerns that excessive reliance on AI might diminish creativity or critical thinking:

> "When we ask it to write for us, it's not our creativity … we don't want to use our own critical thinking" (P4).

Participants also reported a range of emotional responses regarding the use of AI. Sixteen students expressed positive emotions, including *confidence*, *comfort*, and *excitement*, when engaging with AI tools:

> "I was pleased and happy somehow because things became easier to do. It made me feel more confident, more comfortable" (P2).

Fourteen participants expressed *skepticism*, particularly when artificial intelligence generated incorrect or outdated information.

> "ChatGPT only knows information up to two years ago, and sometimes it makes mistakes … I feel suspicious, so I always check with real sources" (P8).

Nine participants articulated the progression of their perspectives on AI over time. One student elucidated:

> "At first, I did not think about integrity … it looked very easy. However, I began to think that it would decrease my creativity if I only used ChatGPT for my writing. My ideas have changed slightly" (P11).

Students also emphasized the accessibility and user-friendliness of AI tools, noting that conversational interfaces facilitated their integration into study routines. However, several participants identified subscription barriers or restricted access as limitations to their utilization.

4.3. *Relatedness: Norms, teachers, and human–AI learning networks*

A third dimension of students' experiences pertained to the *social and normative context* in which AI usage occurred. Within the framework of SDT, *relatedness* is defined as individuals' sense of connection with others and their alignment with shared norms and expectations (Ryan & Deci, 2000).

Sixteen participants expressed concerns regarding *academic integrity* and deliberated on how they differentiated between legitimate assistance and unethical use:

> "There's a line between help and cheating … AI gives me information; it's my job to analyze" (P9).

Twelve participants emphasized the *lack of explicit institutional policies* regarding the use of AI.

> "Some instructors are skeptical and discourage the use of AI, some are very open-minded … University doesn't have a clear and unified policy yet" (P7).

Participants frequently situated AI within an expansive learning network that encompassed teachers, peers, and other resources. Nineteen participants characterized AI as an *assisting tool* rather than a substitute for human instruction.

> "My learning process … teachers [first]; friends; … AI at the 3rd row … AI … helps me … preparing assignments, finding sources" (P15).

Twelve participants emphasized the indispensable role of human instructors in offering motivation and emotional support.

> "I prefer human teachers … teaching is not only about providing information … [teachers] understand emotions and motivate me; AI helps with diagrams and information" (P17).

A subset of students characterized AI as a motivational aid in their academic pursuits.

4.4. Values and broader concerns

In addition to immediate academic practice, some participants considered broader ethical and societal implications associated with the use of GenAI. Seven participants expressed concerns regarding *privacy* and *data protection*, whereas three underscored the potential for bias in the AI training data.

Furthermore, *environmental sustainability* emerged as a concern for several students, with six participants noting that energy and water consumption were linked to large-scale AI systems.

> T1: "Every question that we ask … they are using … water … when I learned that I stopped [and now] use [AI] only when I really need it" (P5).

Furthermore, several participants examined the prospective implications of AI in the context of education, highlighting the *potential benefits* and *risks* associated with an increased dependence on AI technologies.

4.5. Epistemic network analysis

To investigate the structural interconnections among the themes identified through thematic analysis, we performed an exploratory epistemic network analysis (ENA) on 1015 paragraph-level stanzas derived from 23 interviews. Of these stanzas, 23.0% contained two or more co-occurring codes, with an average of 0.95 codes per stanza. A permutation test (N = 500) revealed that the overall co-occurrence structure significantly deviated from random expectations (p = .002), indicating that the relationships among themes in the students' discourse were *systematically patterned* rather than random.

In the ENA model, each interview is considered an individual case, with networks constructed based on the stanza-level co-occurrence of thematic codes. Nodes represent analytical subthemes, whereas edges denote the weighted strength of their co-occurrence within discourse segments. These associations are interpreted as structural relationships within students' reasoning rather than causal effects (Shaffer et al., 2016). While thematic analysis identifies the primary dimensions of students' experiences, ENA offers a complementary analytical perspective by modeling the interconnections of these elements within participants' discourse.

From the perspective of SDT, this approach enables the examination of whether themes related to *competence*, *autonomy*, and *relatedness* that are identified through qualitative analysis also manifest as systematic co-occurrence patterns in students' reasoning about AI-supported learning. In this context, ENA explains how motivational and normative considerations are integrated into students' narratives, rather than appearing as isolated themes.

Fig. 2 presents the resulting epistemic network, which illustrates the most prominent co-occurrence relationships among the identified themes.

The network analysis reveals a central cluster that interconnects *conceptual* support, *skill development*, and *prompting/personalization*, all of which exhibit strong associations with *cross-checking with sources*. This configuration indicates that when students discussed the use of AI as a learning aid, they frequently described concurrent efforts to verify the reliability of AI-generated information. Interpreted through the framework of SDT, this pattern reflects students' endeavors to maintain

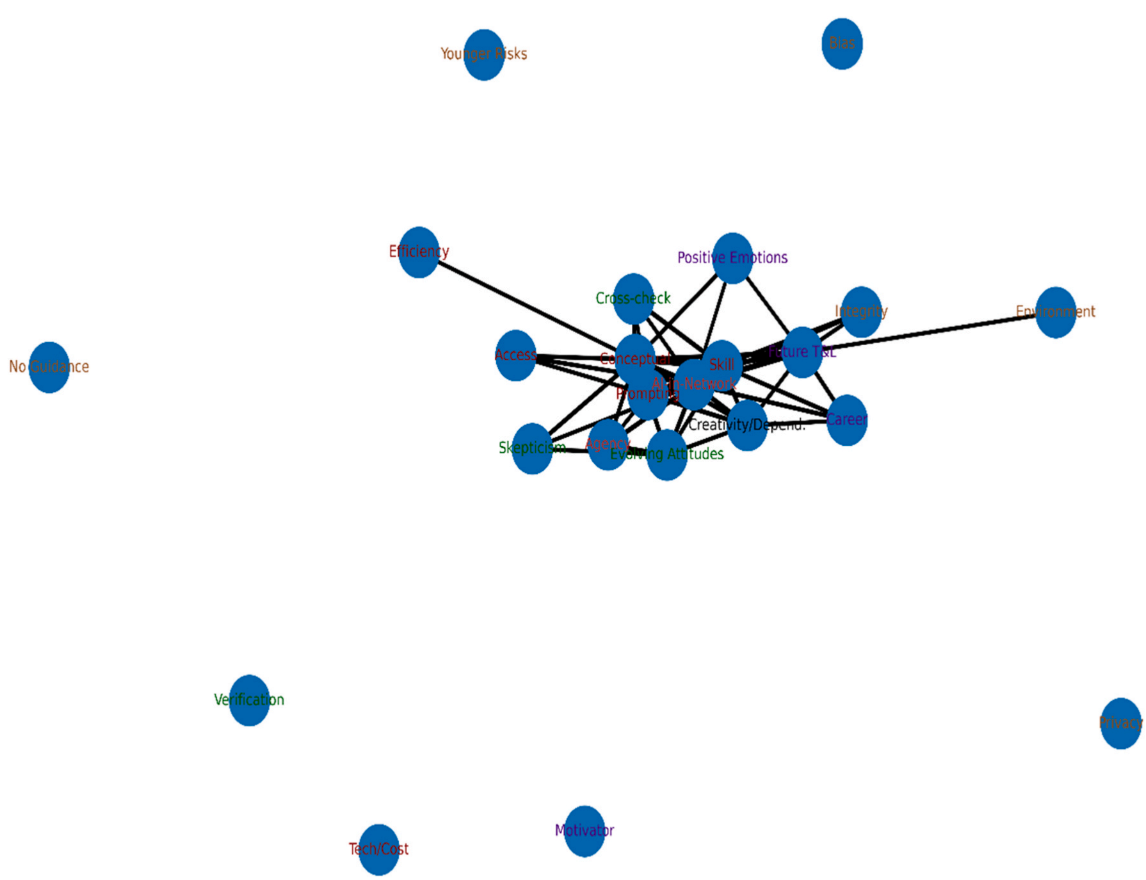

Fig. 2. Epistemic network of co-occurring themes in students' discourse on GenAI use.

perceived competence by integrating AI-supported explanations with evaluative verification strategies. Rather than entirely delegating cognitive tasks to AI systems, participants described incorporating AI outputs into active learning processes that involved monitoring accuracy and ensuring conceptual understanding.

A second significant relationship within the network pertains to the co-occurrence of *creativity* versus *dependency* with verification practices. When students articulated concerns regarding excessive reliance on AI tools, they frequently described strategies aimed at preserving their intellectual autonomy. These strategies included attempting tasks independently prior to consulting AI or verifying AI-generated responses against external sources. From an SDT perspective, this pattern can be interpreted as *a negotiation of autonomy* in which students endeavored to balance the efficiency provided by AI tools with a desire to maintain ownership of their learning processes and cognitive contributions.

The network structure further clarifies the associations involving *integrity*, *risks for novice/younger learners*, and *the future of teaching and learning*, indicating that ethical considerations are frequently interwoven with broader reflections on educational norms and responsibilities. These connections imply that students perceived AI use not merely as an individual efficiency decision but as a practice embedded within institutional expectations and shared academic values. In terms of SDT, such discussions can be interpreted as *expressions of relatedness* that reflect students' awareness of the social and normative contexts shaping acceptable AI use.

The quantitative strengths of these associations are summarized in Table 4, which compares the observed and expected co-occurrences of the most prominent code pairs.

Several relationships occur with significantly greater frequency than would be anticipated under conditions of independence. For example, the co-occurrence of *skill development* with *cross-checking with sources* is more frequent than expected (13 observed vs. 5.31 expected; lift = 2.45; p = .002), suggesting that students often discuss the benefits of learning in conjunction with verification practices. Similarly, the strong association between *conceptual* support and *skill development* (38 vs. 17.68; lift = 2.15; p = .002) indicates that participants perceive AI as facilitating iterative learning processes rather than merely producing completed outputs.

The significant association between *creativity/dependency* and *verification* (lift = 4.71; p = .004) further elucidates how concerns related to *autonomy* and *overreliance* are frequently accompanied by strategies aimed at maintaining epistemic control. These patterns reinforce the interpretation that students' engagement with GenAI involves a continuous negotiation between efficiency, independent thinking, and responsible academic practice.

Additionally, *privacy concerns* emerged as a relatively peripheral node in the ENA network. Although several participants expressed concerns regarding privacy, these reflections were generally considered in isolation from learning practices or verification routines, which accounts for their marginal position within the co-occurrence network. This pattern helps explain the contrast between the qualitative prominence of *privacy concerns* in some interviews and their limited structural centrality within the co-occurrence network.

Collectively, the ENA results expand the thematic analysis by illustrating that students' reasoning regarding AI utilization systematically incorporates *instrumental*, *motivational*, and *ethical considerations*. Specifically, the network structure clarifies how *competence-related learning practices*, *autonomy-related concerns about dependency*, and *relatedness-related discussions of academic norms* frequently co-occur within students' discourse. These findings substantiate the interpretation that students' engagement with GenAI is best comprehended not as a mere technology acceptance decision but as a motivated and socially situated learning practice influenced by the interaction of autonomy, competence, and relatedness.

5. Discussion

The analysis of UG students' accounts revealed that their engagement with GenAI cannot be adequately described as a simple matter of "*acceptance*" or "*rejection*." Instead, students reported a *motivated*, *value-laden*, and *socially situated engagement*, wherein they continuously negotiated *agency*, *competence*, and *academic norms* while integrating AI into their study practices. Interpreted through SDT, these accounts illustrate how AI-supported learning is influenced by the satisfaction and tension of the psychological needs for *competence*, *autonomy*, and *relatedness* (Deci & Ryan, 2000; Ryan & Deci, 2000).

To complement the qualitative thematic analysis, this study also employed exploratory ENA to examine the structural relationships among themes in students' discourse. The ENA results indicated that co-occurrences among key themes were unlikely under a permutation-based null model (p = .002), suggesting that *students' reasoning about AI use formed systematic patterns rather than isolated perceptions.*

5.1. Competence: AI as a resource for learning and verification

The principal finding of this study pertains to the manner in which students incorporated AI tools into their learning practices to enhance comprehension, skill development, and academic efficiency. The ENA identified a cluster linking *conceptual* support, *skill development*, and *prompting practices*, indicating that students frequently employed AI to *scaffold* their learning processes. From the perspective of SDT, these patterns reflect efforts to cultivate *perceived competence*, as students utilized AI-generated explanations and iterative prompting to clarify concepts and refine their understanding.

Competence-related benefits were seldom described without reference to verification practices. Students frequently reported *cross-referencing* AI-generated outputs with course materials, textbooks, or external sources. The ENA results demonstrated a systematic co-occurrence between *learning*-support themes and *cross-checking* behaviors, suggesting that verification was integrated into students' epistemic routines rather than serving as an occasional safeguard.

The pattern, termed "*trust but verify*" in this study, can be interpreted as a form of *competence protection*. Students aimed to leverage the efficiency of AI assistance while retaining responsibility for assessing the accuracy and justification of knowledge claims. These findings align with research on digital information literacy, which emphasizes practices such as *lateral reading* and *source triangulation* as strategies for evaluating online information (Caulfield, 2019; Wineburg & McGrew, 2017). In this context, AI use did not supplement evaluative judgment but instead prompted students to adopt new forms of *credibility assessment* in AI-supported learning environments.

5.2. Autonomy: Negotiating agency and dependency in AI-supported learning

The students' narratives revealed the ongoing negotiations

Table 4
Over-represented co-occurring code pairs in exploratory ENA.

Code A	Code B	Observed	Expected	Lift	p	SDT Interpretation
Skill Development	Cross-checking	13	5.31	2.45	0.002	Competence protection
Creativity/Dependency	Verification	4	0.85	4.71	0.004	Autonomy regulation
Integrity	Risks for Novice	4	0.99	4.03	0.012	Norm internalization (Relatedness)

concerning *autonomy* in their interactions with AI tools. Although the participants recognized the productivity advantages offered by AI, they concurrently expressed apprehensions regarding *dependency*, *diminished creativity*, and *reduced critical thinking*. These concerns underscore the tension between immediate efficiency and the development of long-term competencies.

From the perspective of SDT, this tension can be interpreted as a *negotiation of autonomous regulation*. Students reported employing strategies such as attempting tasks independently prior to consulting AI or verifying AI-generated outputs to ensure that they maintained ownership of their work. The findings from ENA corroborated this interpretation by demonstrating a strong association between discourse related to *dependency* and *verification practices*. When students voiced concerns about *overreliance*, they frequently described behaviors aimed at preserving cognitive agency.

These patterns are consistent with the broader literature on *cognitive offloading*, which posits that external tools can reduce cognitive effort if used uncritically but can also facilitate learning when integrated with reflective monitoring and deliberate practice (Risko & Gilbert, 2016). These findings suggest that students were not passively delegating cognitive tasks to AI systems; rather, many actively experimented with strategies to balance efficiency with independent thinking.

5.3. Relatedness: Norms, teachers, and the social context of AI use

The third dimension of students' experiences pertained to the social and normative context in which AI usage occurred. Participants frequently situated AI within a broader learning network that encompassed teachers, peers, and traditional academic resources. When analyzed through the lens of SDT, this pattern reflects the role of *relatedness* in influencing students' engagement with technology.

Students consistently underscored the *indispensable role of human instructors* in providing *motivation*, *ethical guidance*, and *emotional* support. These perceptions align with evidence indicating that teacher–student relationships are strongly associated with engagement and academic achievement (Roorda et al., 2011). Rather than perceiving AI as a replacement for educators, participants described a complementary relationship in which AI offered informational or procedural assistance, while teachers continued to fulfill relational and normative functions.

Relatedness was also evident in students' discussions of *academic integrity* and *institutional norms*. Participants frequently described navigating ambiguous expectations regarding acceptable AI use. ENA patterns linking *integrity-related* discourse to concerns about *novice learners* and the *future of education* suggest that ethical considerations are embedded within broader reflections about *collective responsibility* and the evolving norms of academic work.

From an SDT perspective, these discussions can be interpreted as *processes of* norm *internalization*, in which students attempt to reconcile *personal values*, *peer practices*, and *institutional expectations* (Ryan & Deci, 2000). These findings underscore the importance of clear *institutional guidance* in supporting students' *ethical engagement with AI* technologies.

5.4. Educational implications: SDT-aligned pedagogy for AI-supported learning

The findings have several implications for educational practice. First, instead of prohibiting AI tools outright, institutions may benefit from implementing autonomy-supportive policies that establish clear boundaries while permitting students to exercise informed judgment in their use of AI. According to SDT, such a structured choice fosters *intrinsic motivation* and *responsible decision making* (Deci & Ryan, 2000).

Second, educators should explicitly scaffold their competence in verification practice. The "*trust-but-verify*" pattern identified in this study suggests that students are already developing strategies to evaluate AI-generated information. Instructional practices, such as *verification logs*, *annotated source checks*, and *reflective explanations of AI use*, could transform these informal practices into teachable academic literacy.

Finally, the integration of learning analytics approaches such as ENA offers opportunities to examine how students' reasoning integrates *instrumental*, *ethical*, and *motivational* considerations. When employed transparently and ethically, such approaches may assist educators in identifying patterns in students' learning processes and provide targeted support for responsible AI engagement.

Collectively, these findings suggest that student engagement with GenAI is best understood as a *motivated* and *socially embedded* learning practice shaped by interactions of *competence*, *autonomy*, *relatedness*, and *institutional norms*. By aligning pedagogical design with these motivational dynamics, teachers can better support students in navigating the opportunities and challenges associated with AI-supported learning.

6. Conclusions

This study investigated undergraduate students' engagement with GenAI in academic learning by interpreting their experiences through the framework of SDT. Rather than depicting AI use as a straightforward decision of technology acceptance, the findings indicate that students' engagement with GenAI is a *motivated* and *socially situated* learning practice, shaped by ongoing negotiations of *autonomy*, *competence*, and *relatedness* (Deci & Ryan, 2000; Ryan & Deci, 2000).

Students frequently described GenAI as valuable for efficiency and conceptual support; however, these instrumental benefits were accompanied by ambivalence regarding creativity, trust, and academic integrity. The participants did not merely adopt AI tools without consideration. Rather, they engaged in reflective decision-making processes to assess when and how AI assistance was congruent with academic objectives and standards.

In addition to thematic analysis, ENA provided structural evidence that the key themes in students' discourse were systematically interconnected. The observed co-occurrence structure exceeded chance expectations under a permutation-based null model ($p = .002$), indicating that students' reasoning about AI use involved patterned associations rather than isolated concerns. In particular, ENA revealed strong connections between *learning*-support discourse and *verification practices*, suggesting that students frequently integrated AI assistance with strategies aimed at maintaining epistemic control over information sources (Shaffer et al., 2016).

Moving beyond narrow acceptance-oriented perspectives, the findings highlight several domains consequential to higher education pedagogy and governance. First, *verification* and *trust calibration* have emerged as essential literacies for managing epistemic risk in AI-assisted learning environments. Second, students' ethical reflections extended beyond plagiarism to include *privacy*, *bias*, and *environmental sustainability*, indicating a broader values-based negotiation of what constitutes legitimate academic work. Third, students consistently situated AI within a distributed learning ecology in which teachers remained central sources of guidance, motivation, and relational support. Finally, within the reform-oriented institutional context examined in this study, *policy ambiguity* appeared to shift responsibility toward regulating AI use among individual students, creating inconsistent norms and uncertainty.

Taken together, these findings support a shift from *prohibition-oriented responses* to *transparent institutional guidance*, *curriculum-integrated AI literacy*, and *assessment practices that foreground learning processes rather* than simply final outputs. Process-oriented assessment strategies, such as staged drafts, AI-use disclosure statements, and structured verification routines, can help make students' reasoning visible while supporting responsible AI engagement. Although this study is contextually grounded in a single institution, the convergence of qualitative thematic insights and ENA-based structural analysis provides a strong foundation for pedagogically informed approaches to AI integration in higher education.

6.1. Implications for practice and policy

The findings indicate that in environments where institutional policies regarding AI usage are insufficiently developed, students frequently engage in AI-assisted learning through informal and inconsistent norms. This highlights the necessity for *transparent governance frameworks* that clarify expectations while promoting *responsible* and *reflective AI utilization* (Miao & Holmes, 2023).

First, institutions should formulate explicit, task-specific guidelines explaining the acceptable uses of GenAI across various academic activities (e.g., brainstorming, drafting, coding, and data analysis). Such guidelines can mitigate ambiguity and empower students to make informed decisions regarding AI usage.

Second, *AI literacy* should be incorporated into the curriculum as a fundamental academic competence. Instruction should encompass not only technical interaction with AI systems (e.g., prompting practices) but also *critical evaluation*, *verification strategies*, and *ethical reasoning* concerning *bias*, *privacy*, and *academic integrity*.

Third, assessment practices should be restructured to emphasize learning processes rather than only the final outputs. Approaches such as staged drafts, brief oral components where appropriate, and reflective AI use logs can assist instructors in evaluating students' reasoning and decision-making processes while discouraging unreflective reliance on AI-generated content.

Finally, according to SDT, *governance* and *pedagogy* are most effective when they support the *psychological needs* for *autonomy*, *competence*, and *relatedness*. Policies that integrate clear expectations with opportunities for responsible choices, explicit instruction in verification practices, and shared norms of ethical AI use are likely to foster more sustainable and developmentally supportive forms of AI-assisted learning.

6.2. Recommendations for practice

Based on the findings, several practical measures can facilitate the responsible integration of GenAI in higher education:

- **Task-Specific Guidelines**: Universities should offer task-specific guidelines that explain acceptable AI usage in activities such as brainstorming, drafting, and coding.
- **Integration of AI literacy into the curriculum**: Instruction should encompass not only prompting practices but also verification strategies, bias awareness, and ethical reasoning.
- **Redesign of Assessments to Emphasize Process**: Assessment formats, such as staged drafts, AI use reflections, and verification logs, can make students' reasoning visible and discourage uncritical reliance on AI.
- **Embedding Verification Practices into Academic Tasks**: *Credibility-checking strategies* (e.g., lateral reading and source triangulation) should be incorporated into rubrics and learning activities.

6.3. Limitations and future research

The findings of this study should be interpreted with caution, given several limitations. First, although the sample comprised students from various disciplines and academic years, the study was conducted at a single English-medium university in Azerbaijan. The institutional context, including the lack of formal AI governance policies at the time of data collection, may affect how students perceive and utilize AI tools. Therefore, caution should be exercised when generalizing these findings to other institutional or cultural contexts.

Second, the rapid advancement of GenAI technologies implies that the findings represent a time-specific snapshot of student perceptions and practices within a swiftly evolving technological landscape. Consequently, future research should revisit similar questions as AI systems, institutional policies, and pedagogical responses continue to develop.

Methodologically, the ENA component of the study was exploratory, utilizing paragraph-level segmentation and dictionary-based coding to identify thematic relationships. Although validation procedures have been employed to enhance the alignment between automated and manually coded segments, dictionary-based approaches remain susceptible to contextual ambiguity, including negation or metaphorical language. Future studies could enhance the robustness of ENA models by incorporating larger proportions of fully human-coded data and segmentation strategies more closely aligned with interview prompts.

Finally, future research could benefit from longitudinal and mixed methods designs that integrate qualitative inquiry with additional forms of learner data, such as prompt logs, annotated drafts, or verification checklists, collected with informed consent. Such approaches could elucidate how students' verification practices, autonomy negotiations, and ethical reasoning evolve over time as institutional policies and AI technologies continue to progress.

CRediT authorship contribution statement

Razia Isaeva: Writing – original draft, Software, Investigation, Formal analysis, Data curation, Conceptualization. **H. Nuran Caner:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Formal analysis. **Mustafa Caner:** Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation. **Louie Giray:** Writing – original draft, Supervision, Resources, Project administration, Methodology. **Engin Karadag:** Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization.

Informed consent

Informed consent was obtained from all individual participants included in the study.

Open data and ethics statement

This study was approved by the Ethics Committee of the Institution (ID: 5736). Informed consent was obtained from all participants, and their privacy rights were strictly observed. The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Ethics Committee

Kadir Has University Ethics Committee for Humanities.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author(s) used Paperpal to refine the language and linguistic aspects of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as necessary and took full responsibility for the final version of the published article.

Declaration of competing interest

Both authors declare that they have no conflict of interest.

Appendix. Evidence Crosswalk

Theme	Sub-theme	RQ(s)	Interpretive Dimension	Representative quote	Freq (n/23)
Learning Support	Efficiency & Time Saving	RQ1	Competence – learning efficiency	"Artificial intelligence plays a crucial role … to save our time … [with AI] two or 3 min; by myself, I would probably spend 1 h" (P2)	19
Learning Support	Conceptual Support	RQ1	Competence – conceptual understanding	"I uploaded some PDF files and asked it to make like 60 questions … it made me understand the topic better." (P12)	15
Learning Support	Skill Development	RQ1	Competence – skill practice	"I use ChatGPT mainly to understand difficult topics, help with writing essays, coding problems if I am stuck, and finding ideas for presentations." (P1)	12
Autonomy & Agency	Creativity vs. Dependency	RQ1	Autonomy – maintaining cognitive agency	"When we ask it to write for us, it's not our creativity … we don't want to use our own critical thinking." (P4)	8
Access & Usability	Accessibility	RQ1	Autonomy – tool accessibility	"It was very easy … I have the PDF on one side and ChatGPT on the other …" (P7)	18
Access & Usability	Prompting & Personalization	RQ1	Autonomy – strategic interaction	"Prompt engineering has become a huge occupation …" (P9)	13
Access & Usability	Technical/Subscription Barriers	RQ2	Practical constraint	"After 5–6 messages it asks for the paid version …" (P6)	8
Autonomy & Agency	Positive Emotions	RQ2	Autonomy – motivational engagement	"I was pleased and happy somehow because things became easier to do." (P2)	16
Autonomy & Agency	Skepticism & Distrust	RQ2	Autonomy – cautious engagement	"ChatGPT only knows information up to two years ago … I always check." (P8)	14
Autonomy & Agency	Evolving Attitudes	RQ2	Autonomy – reflective adjustment	"At first, I did not think about integrity … it looked very easy." (P11)	9
Norms & Institutional Context	Academic Integrity	RQ2	Relatedness – shared norms	"There's a line between help and cheating …" (P9)	16
Norms & Institutional Context	Lack of Institutional Guidance	RQ2	Relatedness – policy ambiguity	"University doesn't have a clear and unified policy yet." (P7)	12
Norms & Institutional Context	Privacy Concerns	RQ2	Ethical concern	Concerns regarding the potential exposure of chats in legal contexts. (P7)	7
Norms & Institutional Context	Bias in Training Data	RQ2	Fairness & ethics	Outputs may reproduce stereotypes because of training bias. (P14)	3
Broader Ethical Awareness	Environmental Awareness	RQ2	Societal responsibility	"They are using water … now I use AI only when I really need it." (P5)	6
Broader Ethical Awareness	Future of Teaching & Learning	RQ2	Educational futures	"Some say AI will become instructors … students can become too dependent." (P17)	11
Verification Practices	Verification Practices	RQ1 & RQ2	Competence protection	"If I don't trust, I look at our PDF or a professional YouTube channel …" (P1)	15
Verification Practices	Cross-checking with Sources	RQ1 & RQ2	Competence protection	"First I check my own resource, then official sites …" (P8)	9
Human–AI Learning Networks	Positioning AI among People & Tools	RQ1	Relatedness – learning ecology	"Teachers first; friends; AI at the 3rd row …" (P15)	19
Human–AI Learning Networks	Human vs. AI Agency	RQ1	Relatedness – human support	"I prefer human teacher … teachers understand emotions." (P17)	12
Human–AI Learning Networks	AI as Motivator/ Companion	RQ1	Affective support	"It really gives me motivation back …" (P13)	4
Developmental Implications	Career Redirection	RQ1	Educational trajectory	AI shapes specialization choices. (P19, P23)	2
Developmental Implications	Risks for Novice Learners	RQ2	Developmental concern	AI may undermine creativity among novice learners. (P20–22)	3

Data availability

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

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