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ARTICLE

Examining Student Teachers' Agency in an AI-Supported Learning Environment: Q Methodology Research

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Abstract

Drawing on a socio-cognitive framework, we explored student teachers' agency along intrapersonal, behavioral and environmental dimensions within the context of a classroom management course. The study investigated the enactment of student agency in an AI-supported learning environment using an innovative AI conversational chatbot whose outputs are based solely on curated course material. Using Q methodology, the analysis of 22 Q sorts revealed three distinct factors: (1) *"I got this…just leave me alone"* – self-reliant users confident in their abilities but exhibiting limited ethical awareness and reflective practices, (2) *"Cipherbot is helpful, but…"* – balanced users demonstrating intentional and ethical engagement, and (3) *"A blind date with Cipherbot"* – uncritical users heavily reliant on Cipherbot with diminished agency and criticality. The results are discussed in light of ongoing deliberations on the complexities of preparing student teachers for ethical and agentive GenAI use.

Keywords GenAI · Student teachers · Q methodology · Qatar

Introduction

A common scenario emerging from university classrooms involves students increasingly relying on generative Artificial Intelligence (GenAI) systems to address academic tasks. For instance, during a discussion on assignments at the beginning of

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the semester, a student might ask, "Can I use AI for this?" or an instructor might end the discussion by saying, "Remember, anyone caught using AI will get an F!" Such discourses highlight the growing presence of GenAI in higher education, which simultaneously introduces opportunities for supporting student learning and challenges for maintaining academic values and integrity (Barrett & Pack, 2023; Darvishi et al., 2024; Van Dis et al., 2023). While GenAI tools, such as ChatGPT and similar models, offer students immediate assistance in generating ideas and images, analyzing and evaluating information, refining arguments and crafting polished text, they also raise concerns about transparency, originality and ethical use (Moorhouse et al., 2024; Qadhi et al., 2024; Vetter et al., 2024).

Integrating GenAI systems in the classroom presents opportunities and challenges, making the concept of student agency (Klemenčič, 2017) in these AI-supported learning environments more critical than ever. As educational institutions increasingly adopt GenAI to support personalized and adaptive learning, students must actively navigate these systems to maintain intellectual engagement, originality and ethical practices (Vetter et al., 2024). For faculty, this new GenAI reality necessitates understanding the underworkings of these systems and adapting their teaching practices accordingly. However, the complexity of GenAI systems is quite difficult for the non-specialist faculty to understand fully. As they often lack formal training in computer science or machine learning, faculty may struggle to understand how these systems generate their outputs or replicate the biases from their training data (Chan & Tsi, 2024). The "black box" nature of GenAI raises further questions about accountability, privacy and reliability. Consequently, many faculty have found themselves at a crossroads, where they are required to understand the technical capabilities and limitations of GenAI systems alongside their pedagogical implications, while also ensuring that their students engage with these systems responsibly and ethically (Chaaban et al., 2024), and in ways that encourage criticality and preserve student agency (Chaaban, 2025). Ideally, one ambitious scenario arising within the university classroom would entail students taking ownership of their learning, critically assessing GenAI outputs, and integrating these systems into their academic work without compromising their intellectual engagement, originality and ethical decision-making (Markauskaite et al., 2022; Vetter et al., 2024). However, reports claim that this has not always been the case (Chaaban, 2025; Darvishi et al., 2024).

In the context of GenAI, the concept of student agency in its traditional sense no longer suffices (Markauskaite et al., 2022). Before GenAI, student agency largely entailed students' abilities to work independently and collaboratively, synthesize solutions to problems and produce original work (Chaaban et al., 2021; Du et al., 2022). These processes required students to enact critical thinking, creativity and manual research skills. With the advent of GenAI, the concept of student agency has taken a new meaning, such as distributive agency (Schlagwein & Willcocks, 2023). While the foundational aspects of agency, such as taking initiatives and making decisions, remain intact, the integration of GenAI has introduced a dynamic relationship between agentic systems and agentic students (Adams et al., 2022). This dynamic has resulted in the form of competition over agency, where students must actively retain control over their learning process rather than concede it to GenAI systems that can easily take over tasks that require analysis, synthesis and even creativity (Eaton,

2023; Vetter et al., 2024). In this sense, students are enacting agency and negotiating it within a shared space of decision making and action (Leander & Burriss, 2020). Rather than viewing agency as a zero-sum competition, distributive agency emphasizes collaboration and co-creation, where both students and GenAI agents play a role in achieving course learning outcomes (Leander & Burriss, 2020). However, for this collaboration to happen, students must remain critical and intentional and ensure that their agency is not overshadowed by the efficiency and capabilities of GenAI (Eaton, 2023; Schlagwein & Willcocks, 2023).

While prior studies have explored student agency in traditional and digital learning contexts (Chaaban et al., 2021; Taub et al., 2020), little is known about how agency is enacted in AI-supported environments, particularly in teacher education (Moorhouse et al., 2024). Existing research often overlooks the dynamic interplay between human agency and the agentic capabilities of AI systems. One innovative solution to ease the technical complexities is to ensure that the GenAI system generates relevant and accurate information. This study addresses these gaps by examining how student teachers negotiate their agency when interacting with a state-of-the-art dialogue-based AI chatbot, Cipherbot, within a classroom management course. This study employed Cipherbot in a teacher education program at X university, exploring how student teachers negotiate agency with this GenAI system. This skill is particularly important for student teachers as they prepare to model and teach responsible GenAI use in their future classrooms (Lee & Yeo, 2022; Moorhouse et al., 2024).

Through Q methodology research (McKeown & Thomas, 2013), this study examined student teachers' perspectives regarding their agency while using Cipherbot to complete course requirements. It examined their enactment of student agency along intrapersonal, behavioral and environmental dimensions. While several studies have examined student agency in a university context (Chaaban et al., 2021; Jääskelä et al., 2017; Lyngdorf et al., 2023), little is known about the interactions of student and GenAI agency, with limited research examining student teachers' perceptions of their agency in an AI-supported learning environment (Darvishi et al., 2024; Markauskaite et al., 2022), as well as the meaningful integration of GenAI systems in teacher education (Lee & Yeo, 2022). This study is guided by the following research question: *How do student teachers perceive and experience agency in an AI-supported learning environment?*

This study serves as an example for computer scientists and other faculty who wish to collaborate on diminishing the technical limitations of GenAI systems, while leveraging their potential to enhance university pedagogy. Acknowledging the staggering pace at which GenAI has been adopted, previously unaccounted for by other digital technologies (Moorhouse et al., 2024), we contended that Cipherbot, as an exemplification for GenAI educational platforms, provides an exemplar for innovative GenAI systems that allows faculty some regulation and influence over their courses in comparison to commercial systems. We also contended that student teachers must acquire knowledge and skills to navigate their current and future uses of GenAI and negotiate their agency. This study sheds light on the effects of participating in an AI-supported course at one teacher education program at X university. Due to the disruptive nature of GenAI in the university context (Markauskaite et al., 2022), it becomes imperative to explore how student teachers make sense of their experiences and enact agency.

Literature Review

Conceptualizing Student Agency

Within the educational field, the concept of student agency is considered a key construct that promotes student participation and influence over their learning (Jääskelä et al., 2017; Klemenčič, 2017). In simple terms, student agency refers to learner's capacity to make decisions, take actions and exercise judgment in their best interest and in ways that support their learning, particularly in constructivist learning environments (Campbell, 2012; Chaaban et al., 2021; Lee et al., 2022). In these contexts, student agency is associated with autonomy, ownership, self-regulation and active engagement in learning, emphasizing the need for students to become proactive participants in their educational experiences rather than passive recipients of knowledge (Du et al., 2020). Agentic students can be differentiated from their peers in how they demonstrate will and ability to take initiative and make decisions, employ self-organization and meta-cognitive skills, and bear responsibility for their academic progress (Klemenčič, 2017). These dimensions are particularly relevant in constructivist educational contexts where students are encouraged to engage in self-directed learning and problem-solving activities (Darvishi et al., 2024; Lee et al., 2022).

While seemingly a straightforward concept, student agency has its roots in possibly contentious theories and perspectives. One point of debate lies in whether student agency is considered an individual capacity versus a socially mediated process (Du et al., 2022). On this point, cognitivist approaches contend that agency resides within individuals and is exercised through autonomous choice and will (Ryan & Deci, 2020). In contrast, sociocultural perspectives argue that agency is co-produced within social contexts. It is shaped by past experiences, oriented toward future goals and enacted in the present (Biesta et al., 2015). Bandura's (1986, 2006) social-cognitive approach provides a middle ground in asserting that individuals are neither entirely autonomous nor completely shaped by environmental influences. Bandura views agency as a dynamic interplay between intrapersonal factors and external influences, where self-direction enables individuals to become agentic. Student agency can thus be "achieved by individuals, through the interplay of personal capacities and the resources, affordances and constraints of the environment" (Priestley et al., 2015, p. 19). In this study, we draw on socio-cognitive perspectives in exploring the perceptions of student agency within AI-supported learning environments along three dimensions: intrapersonal, behavioral and environmental. Research supports this multidimensional view, showing that factors such as self-efficacy, motivation, self-regulation, self-evaluation and access to environmental resources, can either facilitate or constrain agency (Huang & Benson, 2013).

The Intrapersonal Dimension

Intrapersonal factors refer to the personal attributes and processes that influence students' sense of agency, including the cognitive, motivational and affective factors (Gao, 2010). Among these factors, self-efficacy, motivation and interest, knowledge and attitudes toward learning have been examined (Du et al., 2022). Self-efficacy, or

the belief in one's ability to succeed, stands out as an important component of student agency. It influences their confidence in setting expectations and goals, taking ownership of their learning and persisting through difficulties (Bandura, 2006). In one study, engineering students viewed self-efficacy as a significant factor in developing their student agency, particularly in intercultural problem-based learning settings, where the belief in their capacity to solve real-world problems enhanced their confidence to take initiatives and actions in ways that enhanced their engagement in their learning (Jiang et al., 2022). Accordingly, students' beliefs in their abilities to achieve learning goals through intentional and planned actions translate into actual learning behaviors and actions (Hatlevik et al., 2018; Shin, 2018). Similarly, motivation, both intrinsic (i.e., personal interest and satisfaction) and extrinsic (i.e., rewards and recognition), plays a role in influencing student agency and driving certain actions that students find interesting and engaging, otherwise selecting passivity (Shin, 2018), thus reinforcing the notion of subjectivity and individuality of the intrapersonal dimension.

In AI-supported learning environments, researchers have also taken an interest in the intrapersonal dimension (Lee et al., 2022). Annamalai et al. (2023) explored university students' interactions with chatbots and their influence on their competence, autonomy and relatedness through self-determination theory. The researchers found these chatbots influential in fostering a non-judgmental space for skill development, providing immediate feedback and enabling students to track their progress. These features enhanced students' motivation and engagement, giving them confidence in managing their learning experiences without fearing judgment or failure. Similarly, Lee et al. (2022) showed the usefulness of an AI-based chatbot in enhancing university students' after-class review processes, particularly influencing their academic performance, self-efficacy, learning attitudes and motivation. The study emphasized the strengths of the GenAI chatbot in providing instant feedback and personalized learning experiences, which prompted students to become more active and confident in their learning. Despite the benefits of GenAI, advancements have received mixed reactions from university students (Chan & Hu, 2023). While university students generally admire these systems for their usefulness and value, some students may feel dissatisfied with the perception that an overreliance on GenAI stifles creativity, critical thinking and agency (Jin et al., 2023). Further, several motivational features of GenAI include time efficiency, convenience and availability. These features prompt students to resort to GenAI at any time and for any question, no matter how trivial (Jin et al., 2023). However, a preference for instructor support for instilling motivation still prevails. GenAI systems will need to garner the same level of trust that students have in their instructors before promoting student motivation (Jin et al., 2023).

The Behavioral Dimension

Behavioral factors encompass a number of proactive actions and behaviors that fall under self-regulative and metacognitive processes (Bandura, 2006), such as planning, monitoring, reflection and evaluation, which students undertake to exercise their agency. This dimension is closely tied to self-directed learning, which involves intentionally setting goals and strategically seeking knowledge and skills (Du et al.,

2022). According to the extant literature, effective self-regulating students can shape their motivational and affective responses by exercising agency through various strategies, such as learning from prior experiences and remaining flexible when circumstances change (Jin et al., 2023). Self-directed learners are aware of their agency as they set academic goals and continuously reflect on their progress, adjust the strategies they use and make informed decisions about how to proceed (Chaaban et al., 2024). They also enact agency by addressing challenges independently and maintaining a collaborative attitude when working in a team setting (Du et al., 2022). In teams, they balance individual and collective responsibilities and adapt to competing demands, such as time constraints and task pressures. Previous studies have emphasized the need for systemic and systematic support to promote self-regulated learning behaviors, especially since students must balance collaborative projects with individual responsibilities in their courses (Du & Naji, 2021).

From a behavioral perspective, AI-supported learning environments have been commended for offering university students various opportunities for self-directed learning (Annamalai et al., 2023; Darvishi et al., 2024; Markauskaite et al., 2022). GenAI can provide personalized pathways for learning, where students initiate chats, monitor generated outputs for accuracy, adjust their questioning techniques and critically reflect on the usefulness of generated outputs based on their academic goals (Jin et al., 2023; Wu & Yu, 2024). They also offer students autonomy over time and space, allowing them the capacity to monitor and control their learning and advance at their own pace without such constraints (Darvishi et al., 2024). However, in cases of abated criticality, university students tend to relinquish their agency and give the GenAI system control over their thinking and, consequently, their learning outcomes (Vetter et al., 2024). In one study, Darvishi et al. (2024) found that students who were assigned to a hybrid human-AI approach for regulating their learning achieved similar results to those assigned an AI-only approach, though they outperformed students using non-AI approaches. The researchers concluded that students tended to rely on GenAI assistance rather than actively learning from it. Nonetheless, it may also be argued that even in such cases, students remain responsible for their submitted work and are obliged to use validation procedures to affirm the accuracy and reliability of their outputs (Van Dis et al., 2023), thus exercising agency in novel forms.

The Environmental Dimension

Lastly, the environmental dimension refers to the external conditions and contexts that influence students' capacity to make autonomous choices and engage in planned actions (Campbell, 2012). This dimension emphasizes the situated nature of learning and the interplay of multiple systems – institutional, spatial, political, societal and cultural systems – that form the learning environment (Lyngdorf et al., 2023). Recent research has emphasized such interplay between students and the structural and cultural aspects of the socio-cultural context (Jääskelä et al., 2017), which includes atmosphere and dynamics, interdependence among students, relationships between students and teachers, and interactions with learning resources (Chaaban et al., 2021; Jääskelä et al., 2017). Students vary in how they navigate these contextual factors, not merely as reactive and passive respondents, but also as proactive agents who

engage in sense-making and interpretations of their learning experiences and relationships with others (Du et al., 2022). Aligning environmental factors with student agency is important in promoting deeper engagement with learning activities.

In this study, student agency is examined within the context of an AI-supported constructivist learning environment, which will carry specific structural and pedagogical implications, such as individual and collaborative tasks and facilitation from the instructor (Chen et al., 2023). In such learning atmospheres, GenAI should be used as part of instruction, rather than a mere tool that students use outside the classroom to complete assignments (Ulla et al., 2023). When students engage with instructors and peers to refine their understandings along with GenAI, a sense of agency is developed by providing multiple opportunities for interactive and constructive feedback (Annamalai et al., 2023; Lee et al., 2022). Researchers warn that the presence of a GenAI-system should not be used as an excuse for lower physical interaction between and among students and instructors (Chen et al., 2023). On the contrary, there becomes an increased obligation to develop a supportive learning environment where feelings of connectedness are necessary for initiating further actions and emotional involvement (Annamalai et al., 2023). While chatbots can mimic human-like interactions, perhaps even give students a sense of connection and involvement, they cannot replace human interactions as they lack emotional depth and relational nuances that are necessary for reciprocal and dialogic relationships between students and teachers, as well as among students (Annamalai et al., 2023).

This framework was adapted from existing literature on student agency in a university context (Chaaban et al., 2021; Du et al., 2022). It represented a departure point for exploring student teachers' agency in an AI-supported learning environment and, more specifically, for exploring their perceptions and experiences with Cipherbot and the factors they considered important for supporting their agency.

Context of this Study

There is not a lack of innovative chatbots documented in the literature (Chen et al., 2023), each presenting distinct features and attempting to "solve" some educational problem, such as enhancing student engagement (Nguyen et al., 2024), language learning (Annamalai et al., 2023) and exam practice and information retrieval (Lee et al., 2022). Notwithstanding the importance of a chatbot's purposes, functions and features, the deployment of GenAI in the university context requires a thoughtful and emergent pedagogy that tackles persistent ethical concerns, including bias in AI algorithms and data privacy, and a consideration of the implications of AI-supported instruction on the student learning experience (Chaaban, 2025; Lee & Yeo, 2022).

To give a glimpse into the GenAI system developed and deployed in this study, we introduce an educational chatbot called Cipherbot (Salminen et al., 2024a) that bases its answers to student questions on learning material uploaded by the instructor (see Fig. 1). Cipherbot exemplifies the integration of GenAI and large language models (LLMs) into education to support students' learning experiences. The chatbot answers students' queries by retrieving data using natural language processing, optical character recognition and vector embeddings. It operates on OpenAI's ChatGPT

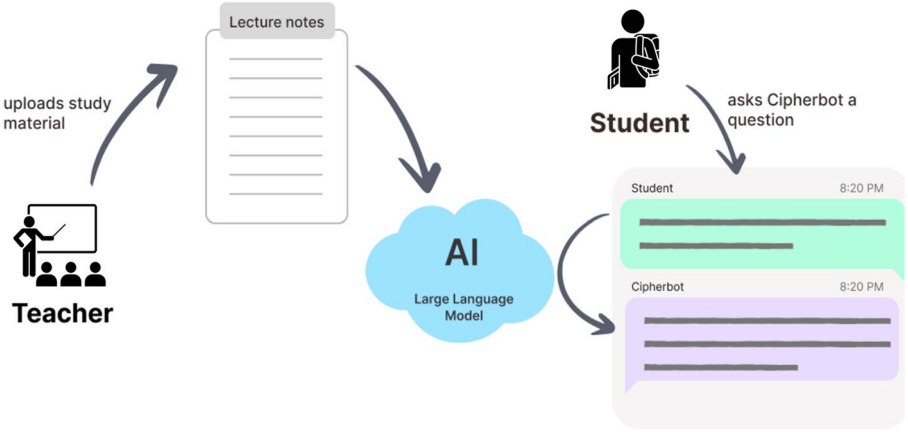

Fig. 1 System overview of Cipherbot (Jung et al., 2025)

4o, and it integrates other technologies, such as Redis Queue, Celery, Azure Storage, Azure Cognitive Search and Azure OpenAI Chat Completions (Salminen et al., 2024a). Unlike many commercial GenAI systems, Cipherbot grounds its responses in the content curated by the course instructor to mitigate the ethical issues of accuracy and relevance. It also tackles the problem of hallucination, where LLMs generate factually incorrect information, by employing a retrieval-augmented generation (RAG) approach, which locates and includes specific information for the LLM to generate its responses and reveals these resources in the chat as available references (Salminen et al., 2024b; Jung et al., 2025). Notable features of Cipherbot relevant to university instruction also include the ability to monitor students' engagement (Salminen et al., 2024b) from frequency reports documenting the number and modes of their conversations, types of questions, and language used, among other characteristics.

Despite these unique features, Cipherbot remains a technology that requires intentional and purposeful use. Knowing the technical underworkings of GenAI allowed the first author to design and implement Cipherbot in her classroom management course. The pedagogy adopted was simultaneously thoughtful and emergent in that the instructor planned and prepared the course syllabus and uploaded 117 resources (i.e., course content) onto the platform ahead of the semester. Adopting an emergent pedagogy allowed the instructor to respond to the dynamic needs of students as they interacted with Cipherbot in real time, both inside and outside the classroom. During instruction, students were prompted to search for information using the chatbot, discuss its responses and share their thoughts with other groups. In other instances, students were asked to respond to scenario-based prompts in groups and then compare their responses with the GenAI chatbot's. Other instructional strategies used inside the classroom entailed prompting Cipherbot to generate scenarios based on a particular classroom management model, request practical suggestions for a particular disciplinary problem or role play with Cipherbot as the teacher or student to simulate certain classroom interactions. These activities aimed to engage students with the chatbot, and model expected criticality and ethical adherence levels.

Outside the classroom, students used Cipherbot to clarify concepts, review learning materials and prepare for assessments. They chose whether to use the chatbot, the frequency of use and the types of questions to ask based on their needs. To promote independent inquiry and self-directed learning, the instructor refrained from imposing the chatbot as a course requirement and remained responsive to students' feedback about its usefulness and efficiency, which entailed changing the pace of engagement with the chatbot, introducing other GenAI systems for comparison and discussing ethical concerns openly. Course assessments included three assignments – school observations, group presentation and behavior management plan – and two exams. Students consulted with Cipherbot on these assessments and generated 2,181 conversations throughout the semester, including 91% topic inquiries compared to 8% follow-ups. A total of 1,852 chats were questions and targeted the following themes: deepening understanding (37%), clarifications on content (34%), discussion of perspectives (11%) and application of knowledge (4%). Cipherbot automatically generates these analytics and provides the instructor with just-in-time statistics on student engagement with the chatbot, which enables timely and informed decisions to enhance student learning.

This study sought to explore student teachers' actions and decisions to exploit the potential of Cipherbot in creating more personalized, adaptive and engaging learning experiences, while also enacting their agency in maintaining academic integrity and ethically sound practices. A key component of this study was the pedagogical approach adopted in the classroom management course, which aimed to leverage the opportunities of GenAI and address the challenges commonly accompanying integrating such advanced technologies into educational contexts.

Methodology

Overview

We employed Q methodology research (Brown et al., 2019; Watts & Stenner, 2012) to explore student teachers' perspectives of their agency in an AI-supported learning environment. Q methodology is an approach that is well-suited for uncovering the subjective and collective perspectives of participants in a systematic and structured way. Combining quantitative and qualitative data collection and analysis procedures, Q is suitable for studies with fewer participants (Watts & Stenner, 2012). A historical account of Q methodology shows how it contrasts with R methodology, commonly used in quantitative studies. In a letter to the journal *Nature*, Stephenson (1935, cited in Stenner et al., 2008) proposed a reversed method to Spearman's conventional factor analysis, suggesting the researchers start with a population of n, each scaled by m individuals, then "the $(m)(m-1)/2$ intercorrelations are factorized in the usual way" (Stephenson, 1936, p. 344). Rather than revealing patterns of associations between a series of measurable variables, Q methodology clusters participants based on the similarities and differences of their perspectives. Accordingly, the factor analysis in Q is by-person, which differs from the by-variable factor analysis commonly employed in R methodology (Watts & Stenner, 2012).

Q methodology was chosen as a methodological approach due to its unique capacity to uncover subjective perspectives and shared viewpoints among participants (Watts & Stenner, 2012). Unlike some other experimental approaches, which typically quantify predefined variables, Q methodology allows for exploring complex, nuanced perceptions that emerge from participants' experiences (Alkhateeb et al., 2022; McKeown & Thomas, 2013). This approach supports the study's aim to understand how student teachers conceptualize and enact agency in an AI-supported learning environment (Moorhouse et al., 2024). By clustering participants based on their perspectives rather than their behaviors or demographic characteristics, Q methodology provides a rich, narrative-driven understanding (Brown et al., 2019) of agency that would be difficult to achieve through experimental means.

Q methodology has been used in various disciplines and has proven to be a rigorous technique for discerning individuals' viewpoints, beliefs, attitudes and opinions (Alkhateeb et al., 2022; McKeown & Thomas, 2013). Following Watts and Stenner's (2012) guidelines for conducting Q studies, we implemented these steps: (1) Q sample development, (2) P set selection, (3) Q sorting activities and (4) Q factor analysis and interpretation. Through this process, the quantitative dimension of Q is manifested in the by-person factor analysis. Yet, t the findings are presented through a qualitative narrative style representing the collective viewpoints of participants loading on a particular factor. Metaphorically speaking, this narrative illustrates the sorts of dialogic deliberations that may have occurred among these participants had they conducted a round-table discussion.

Step 1. Q Sample Development

The first step in a Q study is the development of the Q sample, which is basically derived from a concourse representing all conceivable and interrelated statements generated in response to a particular condition of instruction (Alkhateeb et al., 2022). To generate this concourse, Stephenson (1986) emphasized consulting conversational and informational sources. The former involved informal discussions with students about their perceptions of GenAI, such as frequency of use and value for learning. At the same time, the latter entailed surveying extant literature on a diverse set of research, such as student agency (Chaaban et al., 2021; Du et al., 2022; Lyngdorf et al., 2023) and GenAI in education and ethical considerations (Darvishi et al., 2024; Markauskaite et al., 2022; Van Dis et al., 2023; Vetter et al., 2024). This initial list of statements included 54 statements, which were then categorized, culled and reduced to 37 statements (see Appendix, Table 3), constituting the Q sample for this study. Based on the conceptualization of student agency discussed in the literature review (see subheadings 1.2.1–1.2.3), we categorized the Q sample into three dimensions based on our conceptualization of student agency discussed in the literature review and as shown in Table 1.

Step 2. P Set Selection

Participants were selected strategically as required in Q methodology, as they assumed the status of variables. They were enrolled in the first author's classroom

Table 1 Q sample description

Intrapersonal dimension	Behavioral dimension	Environmental dimension
Statements pertaining to beliefs, self-efficacy, motivation, interest, attitude, knowledge, awareness, intention	Statements pertaining to self-directed learning including goal setting, plan making, monitoring, self-reflection, and ethical evaluation	Statements pertaining to learning atmosphere and dynamics, interdependence, relations between students and instructor, learning resource, criticality, authorship
$N=13$ statements	$N=11$ statements	$N=13$ statements

management course and were instructed to use Cipherbot throughout the semester. Students were informed about the study at the beginning of the semester. Yet, data collection was completed in the final week to ensure students had sufficient experience with the GenAI chatbot, and had formulated informed subjectivities about its influence on their student agency. Due to the limited number of students enrolled in this course ($N=29$), the authors contended that Q methodology would be well-suited as it does not impose large sample sizes nor random selection, which is common in R methodology (Watts & Stenner, 2012). Approval to conduct this study was secured from the IRB committee, where students were enrolled in a teacher education program. The first author informed her students about data collection and invited them to a scheduled session. 22 students attended the data collection day and consented to participate in this study. Having an all-female sample is because male students constitute a small portion of the student population of the teacher education program. Participants' age range was between 21 and 29 and they were either in their junior or senior year of enrollment, which is the typical timing for taking this course.

Step 3. Q Sorting Activities

The participants sorted the 37 items into a quasi-normal and symmetrical grid in response to this condition of instruction: *Student agency can be generally defined as the learners' capacity to act and make decisions that influence their learning experiences. Evaluate whether the following statements are important for supporting your student agency enactment and effective implementation of Cipherbot in achieving the learning outcomes of the classroom management course*. Participants ranked the statements based on their degree of agreement with the statements on a quasi-normal and symmetrical grid (see Fig. 2), with values ranging from −5 (strongly disagree) to +5 (strongly agree), and 0 (neutral) denoting irrelevant responses. The forced distribution procedure guided participants to complete a single and holistic configuration called a Q sort. Following the sorting activity, participants elaborated on the statements they allocated on the extreme ends of the grid. These elaborations offer an interpretative dimension to the Q sort in the participant's words and are used to understand the factor analysis.

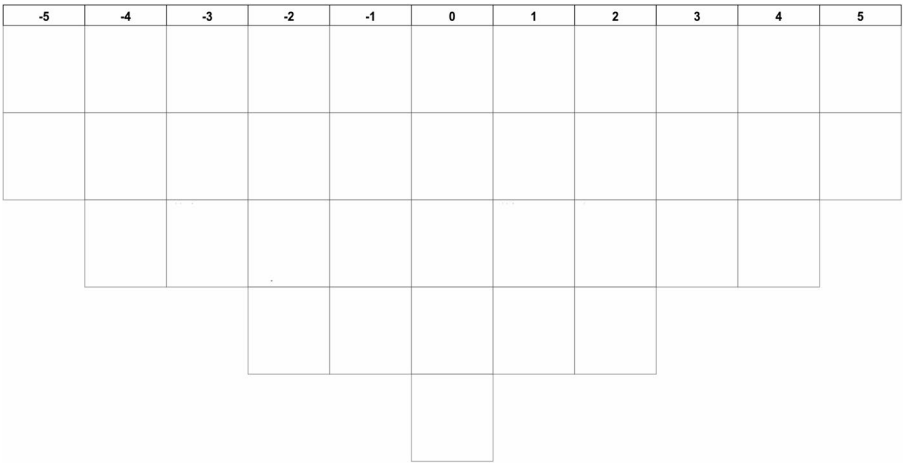

Fig. 2 Sorting grid

Step 4. Q Factor Analysis and Interpretation

The 22 Q sorts collected from participants were imported into KEN-Q software for analysis (Banasick, 2019). Centroid factor analysis was conducted to locate intricate associations among the various Q sorts (Brown, 1980), and varimax rotation was conducted to rotate the factors to a simple structure, representing the collective viewpoints of the participants. We adopted Webler et al.'s (2009) criteria of simplicity, clarity, distinctness and stability in deciding the final number of factors extracted. The z scores for each statement were converted into an idealized Q sort, obtained through a weighted averaging procedure. The explained variance for the factors was calculated by dividing the eigenvalue of each factor by the total variance (sum of all eigenvalues) and multiplying by 100, reflecting the percentage of the variance accounted for by each factor. Three factors emerged through this data analysis, which explained 45% of the opinion variance, as shown in Table 2. We used Brown's (1980) equation to calculate the significance of each Q sort ($p < 0.01$) as follows: $2.58 \times (1 \div \sqrt{\text{the no. of items in the Q-set}})$. Accordingly, 19 of the 22 participants loaded significantly on a distinct factor (± 0.48 at the $p < 0.01$ level), and 3 Q sorts were null cases. As seen in Figs. 3, 4 and 5, these idealized sorts provided detailed information for those statements ranked highest and lowest on the grid, in addition to distinguishing statements across the factors (Watts & Stenner, 2012). The presentation of results constituted a narrative exposition of the participants' viewpoints, offered coherently and holistically, as discussed next.

Table 2 Quantitative summary of emerging factors

Emerging factor	F-1	F-2	F-3	Null
Loading	11	5	3	3
Explained variance	19%	13%	13%	--

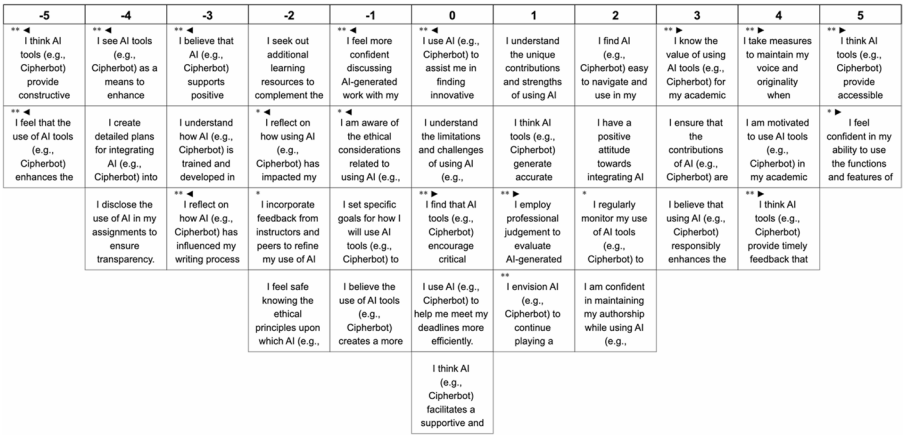

Fig. 3 Factor 1 idealized Q sort

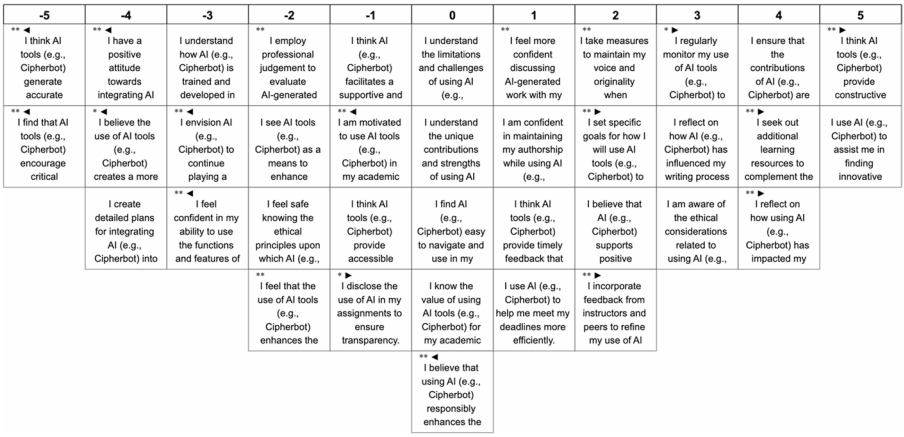

Fig. 4 Factor 2 idealized Q sort

Results

Overview

Table 2 presents a quantitative summary of the extracted factors, showing the number of participants loading on each factor and its explained variance. The three factors represent distinct viewpoints on student agency shared among those participants who loaded significantly on that factor. We denoted these factors as F-1, F-2 and F-3 respectively. The results are presented in narrative style, which is common for Q studies, and each documented statement is followed by its number and value in parentheses.

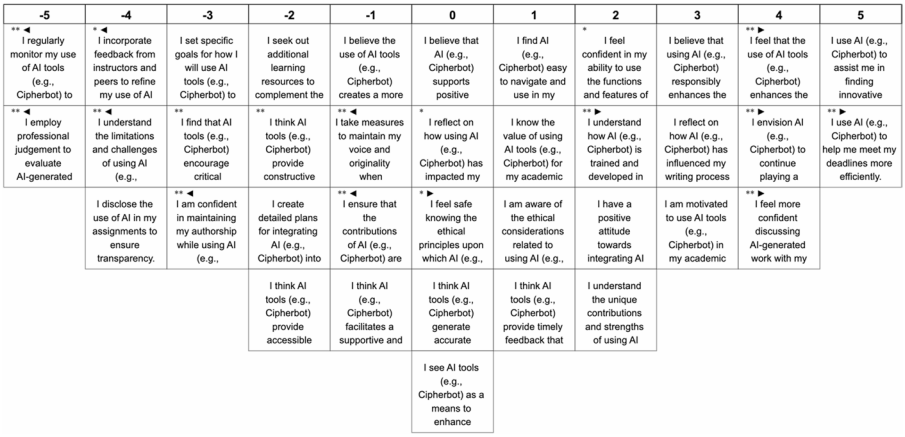

Fig. 5 Factor 3 idealized Q sort

Factor 1: I Got this…just Leave Me Alone

Eleven participants shared the viewpoints expressed in Factor 1 (F-1), explaining 19% of the opinion variance. Figure 3 represents the idealized Q sort for participants loading on F-1. In contrast to F-2 and F-3, these participants possessed intrapersonal characteristics that supported their student agency. A distinctive aspect of this agency was the confidence F-1 participants have in their abilities to use the functions and features of GenAI to enhance their learning (2; +5), their positive attitudes toward integrating GenAI into their academic work (4; +2), and their awareness of the value of these systems for their academic success (1; +3). They seemed to be highly motivated to integrate GenAI into their academic work (3; +4) because they found them easy to navigate and use (5; +2).

Another distinctive source of F-1 participants' agency was their belief in the accessibility of GenAI as resources that support their learning (35; 5). They appreciated GenAI's ability to clarify misunderstandings (36; +4) and enhance the originality and quality of their academic work (7; +3). Such viewpoints revealed the drivers of F-1 participants' agency for using GenAI, yet opened the floor to question the level of criticality enacted and ethical adherence. This observation is based on the notion that F-1 participants were not concerned about inaccurate answers generated by Cipherbot (6; +1), and despite being somewhat confident in their abilities to maintain authorship (33; +2), voice and originality (34; +4), and employ professional judgment while using Cipherbot (17; +1), they were nonetheless, unaware of the ethical considerations related to using this GenAI system in their academic work (10; −1) and did not disclose its use in their assignments to ensure transparency (19; −4).

Was feeling safe knowing the ethical principles upon which Cipherbot is trained and developed (9; −2) sufficient to make them indifferent toward understanding its limitations and challenges for their academic work (12; 0)? This seemed to be the case as they showed negative viewpoints toward self-directed learning approaches. In their daily interactions with Cipherbot, F-1 participants lacked agency in reflecting on how Cipherbot influenced their writing process (23; −3) and how it impacted their

learning outcomes (22; −2). They also failed to create detailed plans for integrating Cipherbot into their study routine (15; −4) and did not consider it useful in helping them meet deadlines more efficiently (18; 0). Such sporadic uses of Cipherbot were coupled with the belief that using GenAI did not necessarily encourage critical thinking and deeper engagement with the course (32; 0), nor was it useful in finding innovative solutions to academic challenges (21; 0), both distinctive statements for F-1 participants.

The "leave me alone" part of the heading given to F-1 emerged from the strong belief that the use of Cipherbot did not enhance the collaborative learning environment in the course (26; −5), nor was it seen as a means to enhance cooperation among students in group assignments (28; −4). Despite the emergent pedagogy adopted in this course, they did not see Cipherbot as supporting positive interactions between students and the instructor (31; −3), nor did they feel more confident discussing AI-generated work with her, despite knowing she understands the system's capabilities and limitations (29; −1). Finally, they rejected the belief that Cipherbot has the potential to facilitate a supportive and inclusive learning environment (27; 0) or provide constructive feedback that helps improve the quality of their assignments (37; −5). These convictions differentiated F-1 participants from their peers and showed the need for pedagogical and ethical deliberations, as taken up in the discussion section.

Factor 2: Cipherbot Is helpful, but…

Five participants shared the viewpoints expressed in Factor 2 (F-2), explaining 13% of the opinion variance. Figure 4 represents the idealized Q sort for participants loading on F-2, who enacted student agency to use Cipherbot within the realm of ethical behaviors and environmental considerations. On the ethical front, they ensured that the contributions of Cipherbot were integrated into their assignments ethically (20; +4). They were aware of the ethical considerations of using Cipherbot in their academic work (10; +2), which distinguished them from other viewpoints. Accordingly, they did not trust Cipherbot to generate accurate answers to their queries (6; −5) and remained apprehensive toward the ethical principles upon which it is trained and developed (9; −2).

F-2 participants enacted several self-directed strategies that revealed their abilities and decisions to overcome these ethical concerns. Unlike F-1 and F-3, F-2 participants set specific goals for using GenAI to complete their assignments (18; +2). They reflected on how the GenAI system impacted their learning outcomes and adjusted their approach accordingly (22; +4). They also reflected on how it influenced their writing process (23; +3) and monitored their use of Cipherbot to avoid completely relying on it for quick answers (16; +3). In a further attempt to remain conscientious of their uses of GenAI, they sought additional learning resources to complement their use of Cipherbot in completing their assignments (24; +4), which contrasted with the viewpoints expressed by F-1 and F-3 participants.

F-2 participants' uses of Cipherbot differed qualitatively from their peers. They were not after quick fixes and used Cipherbot to assist them in finding innovative solutions to academic problems (21; +5) without seeing it as overriding their originality (7; 0). They benefited from the constructive feedback provided by Cipherbot to improve the

quality of their assignments (37; +5). However, they did not rely solely on this feedback; they incorporated further feedback from instructors and peers in their assignments (30; +2). During class instruction, F-2 participants' uses of Cipherbot for several tasks were seen to support positive interactions between students and the instructor (31; +2), but they did not think that it created a more engaging learning environment (25; −4). Other instructional strategies remain to be appreciated alongside the use of Cipherbot, as they disproved the notion that it can encourage critical thinking or deeper engagement with course material (32; −5). Accordingly, they did not envision GenAI to continue to play a significant role in their academic work (13, −3).

So where do these conscientious viewpoints toward Cipherbot and other GenAI systems originate? According to F-2 participants, enacting student agency is not about finding Cipherbot easy to navigate and use in their academic work (0; 5), nor about the value of using it for their academic success (1; 0), nor about feeling confident in their ability to use the functions and features of Cipherbot to enhance their learning (2; −3). From their viewpoints on the ethical considerations of GenAI systems, they were not extremely motivated to use GenAI (3; −1), nor did they have positive attitudes toward integrating them into their academic work (4; −4). These intrapersonal characteristics justify the number of "buts" that F-2 participants had about using Cipherbot in their academic work.

Factor 3: A Blind Date with Cipherbot

Three participants shared the viewpoints expressed in Factor 3 (F-3), explaining 13% of the opinion variance. Figure 5 represents the idealized Q sort for participants loading on F-3. Compared to F-1 and F-2, F-3 participants were peculiar in their uses of Cipherbot in that their agency was almost completely subverted to the GenAI system. Their decisions to use Cipherbot resided in its ability to assist them in finding innovative solutions to academic problems (21; +5) and meet their deadlines more efficiently (18; +5). They believed that using Cipherbot enhanced the originality and quality of their academic work (7; +3). Inside the classroom, they saw the use of Cipherbot as enhancing the collaborative learning environment (26; 4), which was a distinctive viewpoint expressed by F-3 participants. Within this collaborative environment, they felt confident discussing their AI-generated work with their instructor, knowing that she understood the system's capabilities and limitations (29; +4). However, they did not see Cipherbot as enhancing cooperation among students, which indicates a preference for using GenAI inside the classroom or individually outside the classroom (28; 0). Generally, they had very positive attitudes towards integrating Cipherbot into their academic work (4; +2) for these reasons.

This is all well and good until their viewpoints on ethical adherence and self-regulated strategies reveal abated criticality and agency. Quite interestingly, F-3 participants did not employ professional judgment to evaluate AI-generated content for their assignments (17; −5), nor did they regularly monitor their use of GenAI systems to avoid complete reliance on them (16; −5). This is worrisome because they did not understand the limitations and challenges of using Cipherbot for their assignments (12; −4) and were indifferent to the ethical principles upon which Cipherbot is trained and developed (9; 0). Despite reflecting on how Cipherbot has influenced

their writing process and outcomes (23; 3), F-3 participants did not take measures to maintain their voice and originality when incorporating AI-generated content (34; −1). Furthermore, they were least concerned about ensuring that the contributions of Cipherbot were integrated into their assignments ethically (20; −1).

Perhaps due to a lack of confidence in maintaining their authorship while using GenAI for assignments (33; −3), F-3 participants did not disclose the use of GenAI in their assignments to ensure transparency (19; −4). Additionally, they completely relied on Cipherbot's answers and did not seek additional learning resources to complement their use of GenAI (24; −2) or incorporate feedback from instructors and peers to refine their assignments (30; −4). They seemed content with understanding the unique contributions and strengths of using GenAI in their academic work (19; +2) and how Cipherbot is trained and developed in technical terms (8; +2). Consequently, they envisioned GenAI to continue to play a significant role in their academic work (13; +4), despite a lack of goal-setting strategies for how they will use GenAI systems (14; −3).

Discussion

This Q methodology-based research explored student teachers' enactment of agency in a classroom management course at X university. Employing an emergent pedagogy, an AI education chatbot was integrated into the course as an instructional and learning tool. Our choice of Q methodology, rather than other experimental designs (Moorhouse et al., 2024), was intentional as the aim was to reveal the intricate variations among participants concerning the dimensions within which they enacted agency (or not); that is along intrapersonal, behavioral and environmental spaces. The results are represented in three emerging factors, with the following headings: (1) *"I got this…just leave me alone"* – self-reliant users confident in their abilities but exhibiting limited ethical awareness and reflective practices, (2) *"Cipherbot is helpful*, *but…"* – balanced users demonstrating intentional and ethical engagement, and (3) *"A blind date with Cipherbot"* – uncritical users heavily reliant on Cipherbot with diminished agency and criticality. We discuss these factors along the themes, showcased below.

Intrapersonal Factors important, yet Insufficient

As revealed through the viewpoint of F-1 participants, intrapersonal elements, such as motivation, self-efficacy and positive attitudes, are strong drivers of student agency toward using GenAI. Coupled with the ease and value of using these systems for academic work, F-1 participants found Cipherbot to be an asset for clarifying misunderstandings, supporting their learning, and enhancing the originality and quality of their academic work. Previous studies have also commended GenAI's capacity for enhancing engagement and learning (Lee et al., 2022; Jin et al., 2023). Further, the Technology Acceptance Model (TAM) suggests that when users perceive a technology as both easy to use and highly beneficial, their attitudes toward adopting and integrating it into their routines improve significantly (Venkatesh & Davis, 2000). F-1 participants fit this description accurately. Yet, as educators, should we suffice

with students' acceptance of GenAI and applaud their uses indiscriminately? The literature on TAM in an AI-supported learning environment seems to be advocating this approach (Habibi et al., 2023; Li, 2023), yet the results in this study have shown a more nuanced illustration of what could go wrong if we stop at *acceptance*. To clarify this, F-1 participants showed little signs of self-directed learning strategies. Noticeably, they lacked agency in planning and reflecting on the way GenAI influenced their learning and, more specifically, their writing. These behaviors were coupled with a lack of awareness of the ethical considerations of GenAI and a reluctance to disclose its use in their assignments to ensure transparency.

These challenges have been noted in other studies where possessing positive attitudes toward GenAI is often coupled with a lack of awareness of its risks, limitations and negative impacts (Darvishi et al., 2024; Moorhouse et al., 2024; Van Dis et al., 2023). Accordingly, this calls for a critical examination of the factors influencing student agency, knowing that multiple factors are at play, especially in an AI-supported learning environment, where they share agency with GenAI systems unknowingly (Eaton, 2023; Leander & Burriss, 2020). Existing research cannot continue to adopt the same theoretical frameworks, such as TAM, which were developed in a pre-GenAI era, because these frameworks cannot account for the complexities that arise when students start using GenAI systems for the academic work (Markauskaite et al., 2022). They are hyper-agentive machines that can halt students' critical thinking and deeper engagement with coursework, especially since students continue to rely on them despite acknowledging this notion, as did F-1 and F-3 participants.

Reconsidering the Emergent Pedagogy

Despite the emergent pedagogy employed in this study, we were cognizant that teaching and learning are complex, multifaceted processes that are influenced by a myriad of factors, such as the individual differences among students, the instructional design and strategies adopted, and the contextual dynamics that are mostly unpredictable (Du et al., 2020; Jin et al., 2023). This study prompted us to rethink our pedagogical choices as the course developed. In the beginning, we decided to encourage students to use Cipherbot without explicit instruction inside the classroom. Through our regular discussions, we decided that students required explicit "prompting" (pun intended) on how Cipherbot could be used ethically and responsibly. Upon further reflection and discussion, we decided to maintain this component of instructional design consistent throughout the semester.

The first author, who was also the course instructor, discussed ethical decision making, criticality and distributive agency consistently. Nonetheless, most student teachers, including F-1 participants and, in a more evident manner F-3 participants, decided to relinquish their agency to a chatbot, showing indifference about the accuracy of generated answers to their queries. F-3 participants went further in abating their criticality in the presence of GenAI, as they were unconcerned about ethical ramifications, and disengaged in professional judgments and taking measures to maintain their voice and originality when evaluating and incorporating AI-generated content in their written assignments. Despite these violations of academic integrity, we are not suggesting that these students are culprits, as the cognitive appeal

of GenAI is astounding and they may not see where the problem is. The disruptive nature of GenAI in the university context has been substantial (Markauskaite et al., 2022), in addition to mixed messaging from faculty on when and how GenAI can be used, if ever (Barrett & Pack, 2023). Perhaps a unified vision for integrating GenAI within a university context may dissipate students' confusion. However, we caution against the imposition of fixed guidelines that do not account for disciplinary and pedagogical differences across colleges and faculty (Vetter et al., 2024).

Further, F-1 participants and to a lesser extent F-3 participants, could not see the value of GenAI as enhancing cooperation among their peers in group assignments, or supporting positive interactions between students and the instructor, or promoting a collaborative learning environment in the course. According to Annamalai et al.'s (2023) study, GenAI interactions are limited, and without ample opportunities for social interaction, students may feel as though they are learning in a vacuum. The authors of these prior studies attributed their findings to the failure of chatbots to engage students emotionally and cognitively in learning and called for sustained human interactions. Yet, despite the intentional implementation of human interactions in this context, GenAI was discarded by many students as useful in group interactions and of higher value when implemented individually.

Do these results mean that the advent of GenAI will reverse educators' efforts to create collaborative learning environments? This is a viable question to ask at a time when such efforts have always been wrought with difficulties, including students' reluctance to work in groups, the "free ride" syndrome common to many groups, and the extra time and effort needed to make group work truly reap its intended benefits (Du et al., 2020). The introduction of GenAI into the realm of academia will possibly complexify these difficulties and require future research work on how students navigate the boundaries of their student agency and the group's collective agency, in addition to the agentive GenAI system, and how educators should respond (Darvishi et al., 2024; Jin et al., 2023).

More F-2 participants…but how?

F-2 participants provided an ideal scenario for other educators considering ways in which students can integrate GenAI into their academic work without abating criticality or relinquishing agency. These participants were aware of ethical considerations and remained committed to maintaining the originality of their work. They balanced such awareness and commitment with actions and behaviors that revealed intentionality in using GenAI through employing a number of self-directed strategies, such as goal setting, self-monitoring, adjusting and reflection. Rather than seeking quick fixes, these participants saw benefits in GenAI only when it was situated within a positive learning environment inclusive of instructor and peer feedback, interactions and support, corroborating findings documented in Jin et al. (2023). These self-directed learning strategies have been commended in previous research for maintaining agency in decision making while working with GenAI systems (Jin et al., 2023; Markauskaite et al., 2022) and verily found to be a distinctive feature of F-2 participants.

Similarities can be drawn between our F-2 participants and the student from Vetter et al.'s. (2024) study on the level of proactive engagement with GenAI. The student,

much like F-2 participants, maintained a strong commitment to originality and ethical decision making, alluding to the possibility of leveraging GenAI for student success. Yet because of the single case study design in Vetter et al., we could not verify other students' approaches and agentic engagements with GenAI. This comparison is meant to elucidate further the variations among participants documented in this study and show how diverse contexts and instructional designs may shape students' interactions with GenAI, while remaining mindful of the idiosyncratic characteristics of students.

On this note, we documented how F-1 participants' intrapersonal characteristics hindered their agency to engage with GenAI ethically and responsibly, while F-2 participants kept their motivation, self-efficacy, value beliefs and positive attitudes in check. In an AI-supported learning environment, such as the one employed in this study, could these intrapersonal elements be considered adversaries for student agency? These factors have been examined in previous studies and shown to be conducive to student agency (Du et al., 2022; Jääskelä et al., 2017; Klemenčič, 2017). Perhaps the "novelty effect" of GenAI has still not worn off, and students require further instruction and reflection on the limitations and strengths of these systems in an academic setting. This is an area for future research.

Despite the somewhat disappointing results of the emergent pedagogy discussed above, this study calls for a continuation of such pedagogies in the hopes that more students will learn to become like F-2 participants, who provided a utopian example of how student agency can be enacted in an AI-supported learning environment, without compromise. Without clear institutional guidelines, the emergent pedagogy served as a framework for exploring ethical considerations, values and decision making at the localized level of the individual classroom, as advocated by Vetter et al. (2024). This framework showed some signs of success with F-2 participants. However, scaling such success to other students taking the classroom management course and to a broader student population will require further dialogical understandings and negotiations among faculty and students alike.

Conclusion

This study makes three unique contributions: First, it presents an illustrative example of the emergent pedagogy adopted in a university context and the potential of using AI educational chatbots that has been designed to eliminate certain limitations and biases commonly reported about commercial GenAI systems. Second, it offers an empirical understanding of student teachers' experiences with AI educational chatbot, particularly exploring their enactment of student agency in an AI-supported learning environment where the agentic GenAI system may compromise it. Third, contextualizing this study in a teacher education program was intentional because student teachers should be competent, ethical and responsible users of GenAI, as they will then carry such preparation to their future students (Lee & Yeo, 2022). With heightened concerns that GenAI systems will substantially affect teacher education curricula, instruction and assessment (Moorhouse et al., 2024), it becomes imperative that student teachers receive explicit instruction on how to employ GenAI systems critically and effectively in their future classrooms, as well as ethically and agentively.

Appendix 1

Table 3 Z-Score values representing agreement with each statement across factors

#	Statements	F-1	F-2	F-3
1	I know the value of using AI tools (e.g., Cipherbot) for my academic success.	1.26	−0.15	0.32
2	I feel confident in my ability to use the functions and features of AI tools (e.g., Cipherbot) to enhance my learning.	1.56	−1	0.8
3	I am motivated to use AI tools (e.g., Cipherbot) in my academic work.	1.31	−0.38	0.91
4	I have a positive attitude towards integrating AI (e.g., Cipherbot) into my academic work.	0.73	−1.15	0.63
5	I find AI (e.g., Cipherbot) easy to navigate and use in my academic work.	0.84	−0.07	0.35
6	I think AI tools (e.g., Cipherbot) generate accurate answers to my queries.	0.48	−1.94	0
7	I believe that using AI (e.g., Cipherbot) responsibly enhances the originalilty and quality of my academic work.	1.2	−0.24	1.21
8	I understand how AI (e.g., Cipherbot) is trained and developed in technical terms.	−0.94	−0.87	0.74
9	I feel safe knowing the ethical principles upon which AI (e.g., Cipherbot) is trained and developed (e.g., transparency, responsibility, privacy).	−0.77	−0.7	0.03
10	I am aware of the ethical considerations related to using AI (e.g., Cipherbot) in my academic work.	−0.49	0.82	0.3
11	I understand the unique contributions and strengths of using AI (e.g., Cipherbot) in my academic work.	0.48	0.09	0.58
12	I understand the limitations and challenges of using AI (e.g., Cipherbot) in my academic work.	0.16	0.22	−1.39
13	I envision AI (e.g., Cipherbot) to continue playing a significant role in my academic work.	0.3	−0.97	1.41
14	I set specific goals for how I will use AI tools (e.g., Cipherbot) to complete my assignments.	−0.54	0.57	−0.85
15	I create detailed plans for integrating AI (e.g., Cipherbot) into my study routine.	−1.58	−1.26	−0.78
16	I regularly monitor my use of AI tools (e.g., Cipherbot) to avoid my complete reliance on them.	0.65	1.25	−1.55
17	I employ professional judgement to evaluate AI-generated content for my assignments.	0.31	−0.61	−1.68
18	I use AI (e.g., Cipherbot) to help me meet my deadlines more efficiently.	0.05	0.35	1.83
19	I disclose the use of AI in my assignments to ensure transparency.	−1.59	−0.57	−1.41
20	I ensure that the contributions of AI (e.g., Cipherbot) are integrated into my assignments in an ethical manner.	1.25	1.57	−0.45
21	I use AI (e.g., Cipherbot) to assist me in finding innovative solutions to academic challenges.	0.23	1.57	1.89
22	I reflect on how using AI (e.g., Cipherbot) has impacted my learning outcomes and adjust my approach accordingly.	−0.63	1.49	0.06
23	I reflect on how AI (e.g., Cipherbot) has influenced my writing process and outcomes.	−1.12	1.06	0.97
24	I seek out additional learning resources to complement the use of AI (e.g., Cipherbot) in my assignments.	−0.61	1.54	−0.55
25	I believe the use of AI tools (e.g., Cipherbot) creates a more engaging and interactive learning environment.	−0.59	−1.22	−0.36
26	I feel that the use of AI tools (e.g., Cipherbot) enhances the collaborative learning environment in my course.	−1.63	−0.76	1.44

Table 3 (continued)

#	Statements	F-1	F-2	F-3
27	I think AI (e.g., Cipherbot) facilitates a supportive and inclusive learning environment.	−0.26	−0.27	−0.5
28	I see AI tools (e.g., Cipherbot) as a means to enhance cooperation among students in group assignments.	−1.49	−0.65	−0.23
29	I feel more confident discussing AI-generated work with my instructor, knowing my instructor understands the tool's capabilities and limitations.	−0.4	0.46	1.41
30	I incorporate feedback from instructors and peers to refine my use of AI (e.g., Cipherbot) in my assignments.	−0.68	0.54	−1.36
31	I believe that AI (e.g., Cipherbot) supports positive interactions between students and the instructor.	−0.83	0.55	0.23
32	I find that AI tools (e.g., Cipherbot) encourage critical thinking and deeper engagement with course materials.	0.06	−2.05	−0.97
33	I am confident in maintaining my authorship while using AI (e.g., Cipherbot) for assignments.	0.59	0.46	−1.36
34	I take measures to maintain my voice and originality when incorporating AI (e.g., Cipherbot) into my assignments.	1.33	0.61	−0.42
35	I think AI tools (e.g., Cipherbot) provide accessible resources that support my learning.	1.7	−0.53	−0.84
36	I think AI tools (e.g., Cipherbot) provide timely feedback that helps me clarify misunderstandings quickly.	1.27	0.44	0.3
37	I think AI tools (e.g., Cipherbot) provide constructive feedback that helps me improve the quality of my assignments.	−1.61	1.81	−0.7

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Declarations

Competing Interests The authors declare no competing interests.

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