Article

Volume 19 (2026), pp. 37-58
American Journal of STEM Education: Issues and Perspectives
eISSN 3065-1190 | Print ISSN: 3069-0072
Star Scholars Press
https://doi.org/10.32674/t2qnzc90

Talking to machines: How communication style shapes student engagement with AI tutors

Labrado-Antolín, Maribel
Complutense University of Madrid, Spain

ABSTRACT

As artificial intelligence (AI) chatbots become integral to higher education, this qualitative study explores how undergraduate students interact with them during business strategy tasks. Grounded in the Value-Based Adoption Model and utilizing ATLAS.ti for content and co-occurrence analysis, this study analyzes emotional tone and cognitive strategies in 15 student–AI conversations. Students who used a relational tone and followed up with questions demonstrated deeper critical thinking, whereas those who employed neutral tones and passive inquiries showed lower engagement. Co-occurrence analysis highlighted key patterns, such as neutral tone and simple inquiries. Findings suggest that socio-affective alignment in human–AI interaction fosters higher-order thinking, providing pedagogical insights into how AI integration can enhance both cognitive depth and emotional engagement in learning environments.

Keywords: AI literacy, ATLAS.ti, higher education, human-AI interaction, qualitative content analysis, STEM in education, virtual tutor

Editor: Tiago Horta Reis da Silva, King's College London, UK

INTRODUCTION

The increasing integration of AI chatbots in higher education (HE) presents significant opportunities to enhance learning experiences, yet understanding the factors influencing their effective adoption and utilization by students remains crucial (Al-Abdullatif & Alsubaie, 2024). While AI tools offer new opportunities for personalized support and cognitive scaffolding, their pedagogical effectiveness depends on how students interact with them—emotionally, cognitively, and communicatively. This study examines the interaction between university students in a business management course and an AI chatbot during a strategic analysis task. Specifically, it explores whether students' emotional tone and communication style—ranging from neutral to relational—are associated with the complexity and quality of their inquiries. Two research questions guide this inquiry: (1) What type of assistance do HE students seek from an AI chatbot when tasked with analyzing a business strategy, as reflected in the content of their prompts? (2) Which communication tones and inquiry patterns emerge from HE students' interactions with AI during a business strategy analysis?

Given these diverse modes of engagement with AI, selecting a theoretical framework that accounts for utilitarian and affective dimensions is crucial (Kosmyna et al., 2025). Thus, the design of when and how AI-based interventions are to be used in the classroom become of crucial importance to the development of competencies and skills in HE students (Martins et al., 2024). One of the things that distinguishes emerging technologies from their antecessors is the ability to mimic human interactions (Villegas-Ch et al., 2020). Applied in the educational field, these facilitate interactions between the student and information in the form of friendly conversations (Martins et al., 2024). As human-AI conversations become more personalized and agentic, student interaction with chatbots may also shift from transactionally to sociologically and psychologically aligned. Thus, educational AI research needs a new focus on socio-affective alignment between human and AI (Kirk et al., 2025).

AI chatbots are computer applications designed to simulate human-like conversations through text/voice, offering instant and realistic interactions (Usher & Amzalag, 2025). The development of prompt-based AI chatbot by instructors puts the power directly in the hands of instructors who understand the nuances of teaching and learning and the specific contexts of their students and classes (Mollick & Mollick, 2024). These chatbots can understand and respond to student queries, providing synchronous assistance and information about the specific task the students are asked to perform. Thus, the potential of chatbots for learning is promising (Strzelecki, 2024). They can provide rich linguistic input, stimulate student's interest, and contribute to the development of new competencies as well as AI literacy (Kohnke et al., 2023; UNESCO, 2024). Chatbots can support various academic tasks, such as writing dialogue, explaining complex content or summarizing readings, among others (Gill et al., 2024). Through the personalization to the student's proficiency level, the student can engage in tailored learning materials. For HE students, AI chatbot become increasingly interesting to support in higher value add tasks such as organizing ideas, brainstorming ideas, or receiving feedback on drafts (Nguyen et al., 2024).

Despite these advantages, integrating AI chatbots into education brings notable risks. Chatbot responses can be wordy, repetitive, or inaccurate (Kohnke et al., 2023), which can be misleading to users, especially those who are not highly engaged with the task. Often, the connection between the AI-generated information and the original source is lost, even fabricated citations can occur (Kosmyna et al., 2025). These fabricated citations may come unnoticed when critical thinking is not applied. There are also ethical concerns (e.g. fear of cheating) or cultural bias in the source databases and algorithms (Strzelecki, 2024).

The analysis of the student-AI discourse is instrumental in comprehending and interpreting student engagement with the cognitive task (Thimmanayakanapalya et al., 2025). This granular analysis allows for the identification of conversation styles (e.g., neutral, praising, reprimanding, … (Usher & Amzalag, 2025), which are crucial to understand the student's intimacy with the AI chatbot and its potential impact on the quality of the queries placed on the chatbot, resulting in higher quality deliverables.

This study hypothesizes that students who adopt a relational communication tone and engage in follow-up questioning during AI chatbot interactions will demonstrate higher levels of cognitive engagement—reflected in the complexity and strategic depth of their inquiries—compared to those who maintain a neutral tone and rely on passive information consumption. This assumption is grounded in the Value-based Adoption Model (VAM), which suggests that perceived value and emotional alignment with technology influence user behavior and engagement quality.

A challenge particularly relevant to this study is the risk of passive consumption, which can lead to superficial engagement, weakened critical thinking, and a less in-depth understanding (Nguyen et al., 2024). Something that should not escape the educators' eye is the risk that, despite this plausible inaccuracy, most students trust the AI chatbot's ability to provide correct answers (Ding et al., 2023). This study explores undergraduate students' interactions with AI tutors during a strategic business analysis task. Fifteen students engaged in 45-min individual sessions using a structured virtual tutor prompt. Findings contribute to the ongoing debate about the ethical integration of AI in higher education enhancing cognitive engagement and guiding classroom interventions.

LITERATURE REVIEW

The incorporation of emerging technologies, such as AI, is transforming the teaching and learning contexts in HE. In the realm of education, research has delved into the adoption of AI chatbots, social chatbots or AI-based applications, among others in HE and their role in education (Ayanwale & Molefi, 2024; González-González, 2023; Villegas-Ch et al., 2020).

Related work on student-AI chatbot interactions in education increasingly calls for in-depth analysis of actual conversations, moving beyond mere perceptions. Usher and Amzalag (2025) directly analyze the academic writing interactions of graduate students. Their findings indicate students primarily use chatbots as "functional aids" for basic tasks, with higher-order requests being less common, suggesting a tendency towards simpler queries. Further, Thimmanayakanapalya et al. (2025) provide a comprehensive discourse analysis for chatbots, underscoring how the qualitative analysis of the conversations are essential for designing human-like interactions and managing communication complexities relevant to AI chatbots. Reinforcing interaction dynamics, Nguyen et al. (2024) found that a collaborative engagement approach with AI, correlated with better academic writing performance, contrasting with less effective linear approaches.

Understanding the nuances of actual student-chatbot interactions is crucial for optimizing their pedagogical use. Research in this area has begun to categorize how students communicate with these tools. Previous studies analyzing the emotional tone or sentiment in student-chatbot interactions have identified some patterns. First, Usher and Amzalag (2025) found the neutral tone are most frequently used. Characterized by straight forward instructions or factual statements without expression of sentiments. A praising tone is also common, reflecting approval or satisfaction with chatbot responses, often including expressions of gratitude or politeness (Ding et al., 2023). Lastly, the reprimanding tone is typically found the least frequent, conveying dissatisfaction or frustration, particularly when chatbot responses are inadequate, misleading, or lack proper citations (Usher & Amzalag, 2025).

Prior research on student-AI chatbot interaction has largely focused on the use of the virtual tutors for higher order writing tasks. These include support on generating content, extending existing text, concept clarification or text refining) are the types of assistance mostly used (Bibbi

& Atta, 2024; Ding et al., 2023; Gill et al., 2024). Nonetheless, with regards to communication styles, referring the complexity of the queries posted by students, have also revealed differences in the type of assistance requested. Usher and Amzalag (2025) studied student-chatbot interactions for academic writing assistance purposes in 43 graduate students. This pair of researchers found the requesting style characterized by direct appeals for support to be dominant in this cohort of students. Common linguistic patterns identified in this style included phrases like "can you rewrite this paragraph in a more formal tone?" (p. 10), illustrate a direct request for clarification and detailed responses from chatbots. A declarative style (Bibbi & Atta, 2024), where the student provides information without expecting a specific response is, apparently, less present in former studies. The task-oriented nature of chatbots may make this communication style less appealing.

The Value-Based Adoption Model (VAM)

This study necessitates a theoretical framework capable of capturing the subjective, cognitive, and evaluative dimensions of student-AI collaboration (Nguyen et al., 2024). The VAM is an appropriate theoretical lens for analyzing student-AI conversations, particularly those focused on strategic and critical thinking tasks (Al-Abdullatif & Alsubaie, 2024). The VAM is designed to evaluate user intentions regarding technology acceptance through the lens of perceived value (Kim et al., 2020). The central tenet of VAM is that perceived value is a pivotal determinant shaping users' acceptance and use intention. At its core, the VAM posits that the perceived value of technology is determined by a balance between the perceived benefits and drawbacks of using it.

The Technology Acceptance Model (TAM), proposed by Davis et al. (1989), posits that perceived usefulness and perceived ease of use are the two primary factors influencing an individual's intention to use the technology. Although TAM offers valuable insights, it may not fully capture the emotional and relational aspects that shape students' responses to AI tutors, particularly in scenarios that require higher order thinking and affective alignment (Zhao et al., 2025). By contrast VAM incorporates both utilitarian and affective dimensions, providing a more comprehensive understanding of technology adoption in learning environments. VAM extends TAM theoretical scope by shifting the focus from individual feature perceptions to a holistic cost-benefit analysis (Rahman et al., 2025). VAM integrates perceived usefulness, along with perceived enjoyment, as key components contributing to the broader factor of perceived benefits (Liao et al., 2022). VAM distinguishes itself by also introducing perceived sacrifice, which includes perceived risk and perceived fees of using the technology (Al-Abdullatif & Alsubaie, 2024).

Studies on learning technology often employ both models, sometimes extending TAM to include factors like technical competency or behavioral intention to use generative AI models (Wang et al., 2025). The critical difference between TAM and VAM is that VAM explicitly captures the dual nature of AI adoption in HE, providing for a suitable framework to explore how students weigh the psychological and practical trade-offs (sacrifice) alongside the functional efficiencies (benefits), to arrive at an overall perceived value (Kim et al., 2020; Yu et al., 2017). The VAM model provides a more robust explanation of technology acceptance, especially for complex high-stakes tools like AI tutors (Nasni Naseri & Abdullah, 2024).

In the contexts of virtual tutors, the students who perceive the tool as valuable for their learning are more likely to accept the tool and integrate them in their learning practices. The VAM research has revealed a strong and significant relationship between perceived usefulness and perceived value in technology adoption (Yu et al., 2017). Thus, when students perceive value in the AI chatbots, and they perceive these outweigh the associated drawbacks, their perceived usefulness will significantly contribute to the overall perceived value of the virtual tutor. The expectation is then that the communication style with the virtual tutor will be of higher value added to the student's learning. Interestingly, VAM research has also highlighted the benefits from perceived enjoyment. Beyond purely functional advantages, perceived enjoyment captures the emotional benefits derived from interacting with a virtual agent (Kim et al., 2007). Findings from Kohnke et al. (2023) reveal that the perceived enjoyment of using Chat GPT for language learning has a significant positive effect on the perceived value of the tool.

The drawbacks associated with the use of AI chatbots are found in the apprehension of subscription fees or other costs of using generative AI (Al-Abdullatif & Alsubaie, 2024). If the perceived value of using the AI chatbot does not compensate for the perceived fees, students may opt against it. Equally, VAM literature refers to perceived risk of the use of AI. While a growing body of research traditionally suggests an inverse correlation between perceived risks and perceived value in technology adoption (Rapp et al., 2021), studies on gen AI adoption (e.g., ChatGPT) have presented a nuanced understanding. For instance, Al-Abdullatif and Alsubaie (2024) found that perceived risk showed no significant effect on students' perceived value of ChatGPT, possibly due to a normalization of technology-associated risks or a prioritization of the tool's academic utility and efficiency over potential risks.

RESEARCH METHOD

Participants

The study sample consisted of fifteen undergraduate students enrolled in a business management course within the Faculty of Business and Economics at a major public higher education institution during the spring semester of the 2024-2025 academic year. All participants volunteered for the study and gave consent for their chatbot conversations to be analyzed for research purposes. Of the collected data, ten student-AI chatbot conversation transcripts were correctly uploaded for final analysis, reflecting the standard practice of prioritizing qualitative depth over sample size (Rruplli et al., 2024).

Task design and data collection

Participants engaged individually with an AI chatbot to analyze an international business strategy scenario. The instructor designed the chatbot to facilitate the application of strategic frameworks, particularly the CAGE model (Ghemawat, 2001). After a briefing session the students used the chatbot for approximately 45 minutes to explore business strategy issues, generate questions, interpret theories, and conduct company research. Most students selected ChatGPT as their preferred AI tool. Each student's conversation log was shared with the researcher for future analysis.

The students in this study are not tasked to write an essay but to investigate and evaluate the international business strategy undertaken by a real company. The instructor designs the chatbot to guide the students in the use of theories relevant to the business scenario. The development of prompt-based AI chatbot, puts the power directly in the hands of instructors who understand the nuances of teaching and learning and the specific contexts of their students and classes (Mollick & Mollick, 2024). These chatbots can understand and respond to student queries, providing synchronous assistance and information about the specific task the students are asked to perform. In this study, each student engages in individual conversations with the chatbot, voluntarily adopting a research angle.

Qualitative data analysis and coding procedures

Data analysis was carried out using ATLAs.ti, a leading qualitative research software platform suitable for content and co-occurrence analysis of human-AI studies (Paulus et al., 2017a). The transcription of data was coded inductively and deductively, beginning the preliminary codes categories drawn from the literature, and adjusted as themes emerged from the data (Sulatko, 2024). Three coding families were created: assistance sought, communication style and tone, and strategic focus.

For this study, communication style refers to the structural approach students used to frame their interactions with the chatbot, encompassing patterns such as "requesting," "questioning," and "declarative". Communication tone refers to the emotional undertone or sentiment conveyed, identified by patterns such as "neutral," "praising," and "reprimanding". The content of the prompts was categorized into types of inquiries, and these were assessed for their inherent complexity (e.g., distinguishing between lower-order tasks like content generation and higher-order tasks like strategic queries or scenario-based queries).

Documents were segmented into “RELATES” and “NOT-RELATES” groups based on the presence or absence of relational communication codes. Multiple analyses were performed using ATLAS.ti, including code-document frequency and co-occurrence tables, and the construction of network visualizations to map semantic relationships and thematic clusters in the data.

Regarding query complexity and cognitive effort, Kosmyna et al. (2025) observed that the use of Large Language Models use reduced cognitive load and neural activity, potentially fostering metacognitive laziness. This implies that reliance on AI may lead to less cognitively demanding queries. Conversely, Walter (2024) advocates that precise, complex prompts are necessary to elicit specific, useful AI responses. Methodologically, studies like Paulus et al. (2017) and Passonneau and Coffey (2011a) demonstrate the efficacy of qualitative content analysis and discourse analysis, often supported by tools like ATLAS.ti, for systematically coding and analyzing conversational transcripts to uncover patterns in interaction content and dynamics

Each segment of prompt text was marked as a quotation, assigned the relevant code(s) that best reflected its function or sentiment. Coding definitions, criteria for inclusion/exclusion, and hypothetical examples were compiled in a comprehensive codebook, later expanded to include example citations per code.

To ensure rigor, a subset of coded prompts (n=3) was randomly selected for inter-coder agreement validation. Two additional coders independently coded these segments, and Cohen’s Kappa was calculated, yielding high agreement rates (80% and 85), consistent with the established standards for qualitative research reliability (Rruplli et al., 2024).

This methodology is consistent with recent peer-reviewed work using qualitative and mixed-methods approaches to analyze student-AI interactions, including direct content and co-occurrence analysis (Paulus et al., 2017a; Rruplli et al., 2024).

Coding

Coding is like taking notes in the side of the book pages (Passonneau & Coffey, 2011b). Text reflecting different prompt functions (e.g., expressing a communication tone, type of assistance requested to the virtual tutor, …) is marked as quotations which are then attached to category codes (see Figure 1). Whilst one project member was responsible to all manual coding, this was checked upon completion by another project member. Disagreements were discussed and then any necessary changes were made. It took several weeks to adjust the final 21 codes, clear patterns presented themselves. 5 families were created out of the patterns (see Table 1).

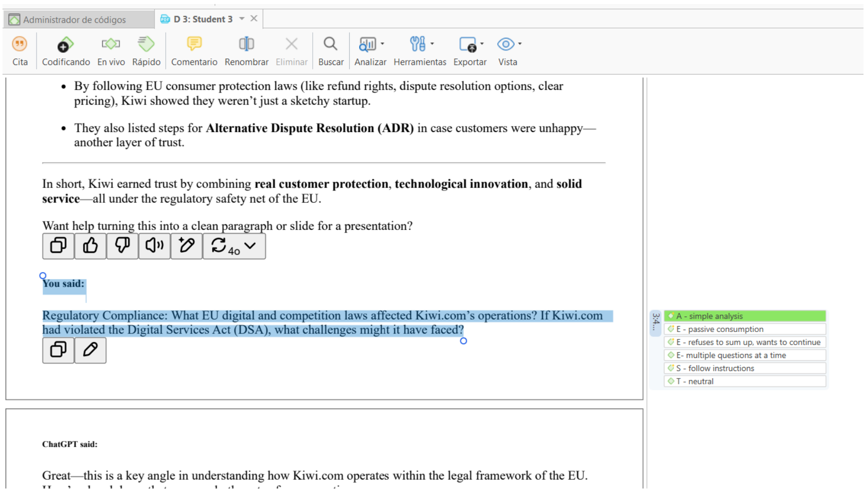

Figure 1- The highlighted text is a prompt quotation to which the specific codes (e.g., simple analysis, passive consumption, …) from different families (e.g., assistance sought, engagement with AI, …)

Thematic analysis of student prompts yielded three overarching code families: Assistance Sought, Communication Style and Tone, and Strategic Focus. The Assistance Sought family includes codes such as "A – critical thinking," "A – simple analysis," and "A – basic facts," reflecting varying levels of cognitive engagement. Communication Style and Tone capture how students interact with the AI, including codes like "E – multiple questions at a time," "E – collaborative," and "T – praising." Finally, Strategic Focus encompasses the thematic orientation of prompts, with codes such as "S – theory applied," "S – focus on future," and "S – external focus." These families provided a structured lens to interpret the nature and depth of student-AI interactions.

A complete code book was written presenting, for each final code its definition, criteria for inclusion or exclusion of the prompts in the code category, as well as hypothetical prompts to exemplify the code category. Once the coding is completed and validated, a final column is added onto the code book including an example of coded citation per category. Table 1 shows the list of code categories and families created for the final research and some of the false start or dead-end codes initially used. Two super families were created. Figure 2 shows the relationship between codes, families and super families.

Table 1 - Illustration of codes and families, and false start groups

	Assistance seeked	Communication style	Communication tone	Strategic focus	False start groups
Codes in alphabetical order	A- critical thinking	E - multiple questions at a time	T - neutral	S - theory applied	AI literacy high
	A - simple analysis	E - follow up	T - praising	S - internal focus	AI literacy med
	A - basic facts	E - passive consumption	T - relate	S - focus on future	AI literacy low
	A-basic context	E - Refuses to sum up, wants to continue		S - curiosity	Reflective question
		E - declarative		S - follow instructions	Summative question
		E- collaborative		S - external focus	
Totals	4	6	3	6	5

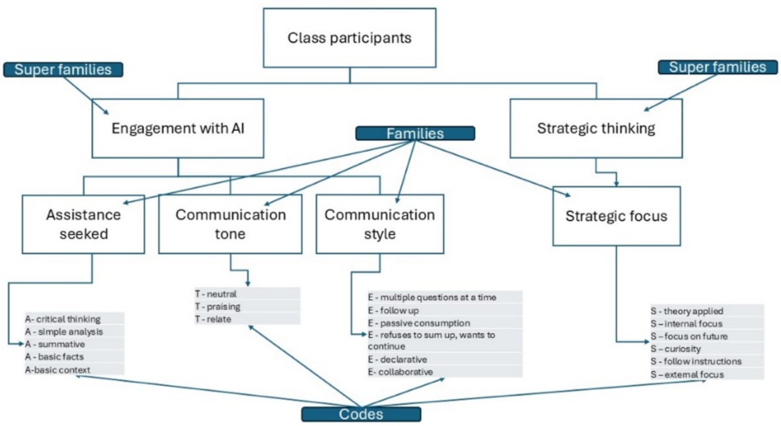

Figure 2 - Codes, families and super families

RESULTS

Several analyses were performed using ATLAS.ti functionalities. Firstly, the documents were segmented into two separate groups. On one end, the student prompts that showed no codification for the T-relate code were grouped into "NOT-RELATES" (30 coded quotations across 6 documents); the remaining were grouped into "RELATES" (34 coded quotations across 4 documents). This segmentation will be useful in the subsequent interpretation of the data.

The frequency of codes per document groups were analyzed separately. The code-document frequency analysis (see Table 2) revealed distinct patterns in how participants engaged with prompts. In the RELATES group, there was a marked increase in codes associated with follow-up questions, collaborative enquiries, critical thinking, focus in future, and relational communication tone. The grounding of these codes in the RELATES group show a relative weight of 80% of higher. In other words, 80% or more of the quotations attached to each of these codes belong to student prompts grouped in the RELATES segment. For instance, the code "Engagement with AI – Follow up" appeared 23 times in RELATES documents compared to only 4 times in NOT-RELATES. Similarly, "E- collaborative" quotations were significantly more prevalent (1 in 5 times) in the RELATES group. Collaborative quotations seem preceded by a certain level of trust in the AI chatbot capacity to provide a trustworthy answer to a relevant question. For example, student 2 stated "What do you think are the future risks or opportunities for Kiwi.com as EU laws evolve?" In this quotation, the student apparently engages with the AI chatbot in a joint thinking process to anticipate both a future scenario (how the EU laws are to evolve) and its consequences (future risks and opportunities).

Table 2 - Code-document frequency heatmap (Document group segmentation).

		NOT-RELATES 6 30		RELATES 4 34		Totales	
A - basic contexts	16	9	56,25%	7	43,75%	16	100,00%
A - basic facts	2	2	100,00%			2	100,00%
A - critical thinking	27	10	37,04%	17	62,96%	27	100,00%
A - simple analysis	34	16	47,06%	18	52,94%	34	100,00%
E - collaborative	6	1	16,67%	5	83,33%	6	100,00%
E - declarative	4			4	100,00%	4	100,00%
E - follow up	27	4	14,81%	23	85,19%	27	100,00%
E - passive consumption	19	15	78,95%	4	21,05%	19	100,00%
E - refuses to sum up, wants to continue	13	4	30,77%	9	69,23%	13	100,00%
E- multiple questions at a time	21	11	52,38%	10	47,62%	21	100,00%
S - curiosity	11	3	27,27%	8	72,73%	11	100,00%
S - external focus	11	4	36,36%	7	63,64%	11	100,00%
S - focus in future	5	1	20,00%	4	80,00%	5	100,00%
S - follow instructions	19	11	57,89%	8	42,11%	19	100,00%
S - internal focus	10	3	30,00%	7	70,00%	10	100,00%
S - theory applied	22	8	36,36%	14	63,64%	22	100,00%
T - neutral	51	28	54,90%	23	45,10%	51	100,00%
T - praising	2			2	100,00%	2	100,00%
T - relate	13	1	7,69%	12	92,31%	13	100,00%
Totales		131	41,85%	182	58,15%	313	100,00%

Conversely, NOT-RELATES documents showed higher frequencies of passive consumption and basic factual engagement, suggesting a more receptive or less interactive stance (see Figure 3). These findings suggest that mimicking human-to-human interaction may stimulate more active, reflective, and relational engagement, thereby enhancing the depth of cognitive and emotional responses elicited by student prompts.

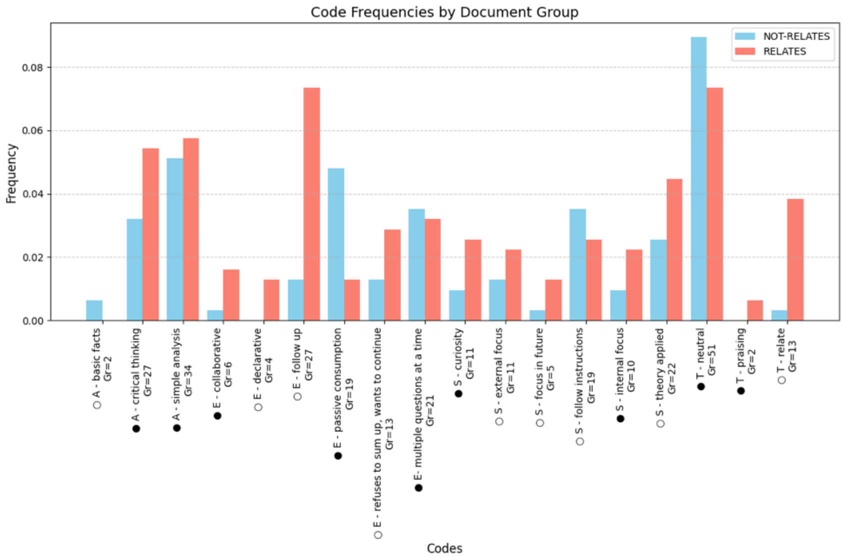

Figure 3 - Code frequency by document group

A detailed analysis of the prevalence of quotations attached to Strategic thinking family codes (e.g., critical thinking, internal focus, theory applied, …) reveals a dominance of strategic thinking in the RELATES document group. Interestingly, only the code "S – follow instructions" shows a higher prevalence in the NOT-RELATES group (see Figure 4). The visual analysis reveals new insights about the cognitive process elicited by the students in both document groups. Prompts where students explore questions beyond the task ("S – curiosity") show a significant higher attachment within the RELATES group. Similarly, questions about future business implications ("S – focus on future") or the effects of the actions in business outcomes ("S – internal focus") are significantly more present in the RELATES document group.

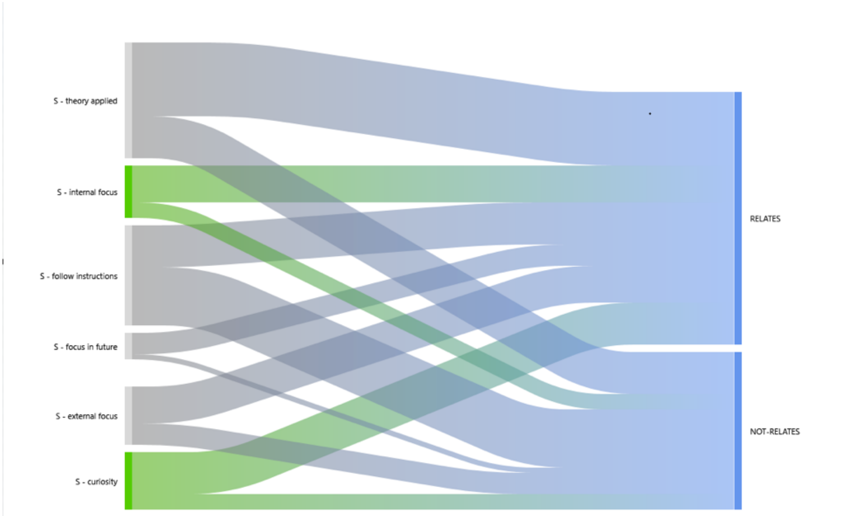

Figure 4 - Sankey diagram - Strategic focus family codes per document group

Similarly, a visual analysis of the Engagement family of codes (see Figure 5) per document group produces a few interesting insights. For example, declarative prompts ("E – declarative") is only attached to quotations from RELATES document group; similarly, a collaborative engagement style with the AI chatbot ("E – collaborative") attachment within the NOT-RELATES group document is very thin. Passive consumption of AI responses ("E – passive consumption") shows a higher grounding in the NON-RELATES group; whereas follow up questions ("E – follow up") has higher grounding in the RELATES group.

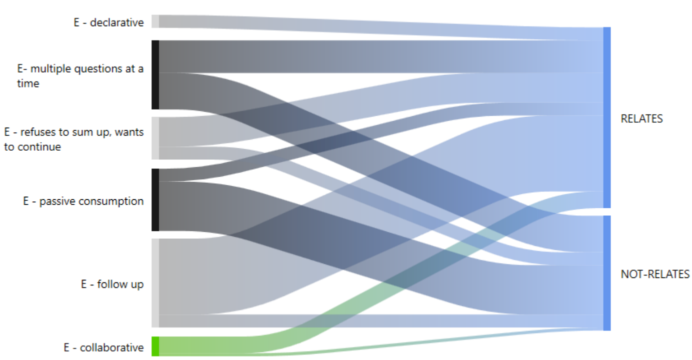

Figure 5 - Sankey diagram - Engagement with AI family codes per document group

Following instructions in the context of this study refers to a close adherence to the instructions provided to complete the task. In many cases, quotations attached to this code are literal prompts copied from the instructions set. For example, student 3 prompted “Market Entry & Growth: Learn about Kiwi.com strategy entering the EU market. Which major barriers did the company to overcome? Reflect on the barriers they encountered and research about the resolution? What role did EU regulatory framework have in Kiwi’s story?”. “S – follow instructions” has a relative high co-occurrence with “E – passive consumption”. An interesting example of this co-occurrence can be found in student’s 7 prompt, where several “next dimension” quotations are repetitively found along the student-AI chatbot conversation.

Secondly, the co-ocurrence analysis reveals significant patterns among the applied code. Co-ocurrence is represented via a table that presents the frequency with which two codes appear together in the same quotation. Each cell indicates the number of times a pair of codes co-occurred. High co-occurrence values indicate a strong thematic relationship between codes. Notably, there is a strong association between the code “T - neutral” and the cognitive codes “A - simple analysis” (31 co-occurrences) and “A - critical thinking” (22 co-occurrences), suggesting that participants tend to express analytical and reflective processes in a neutral tone. Additionally, the co-occurrence between “S - follow instructions” and “E - follow up” (16 co-occurrences) indicates a structured interaction dynamic, where instruction-following is accompanied by responses that deepen or extend the conversation. These findings suggest a relationship between communicative style and the cognitive processes elicited by the use of prompts in the analyzed context.

Overall, the highest prevalent code categories are, in descending order: neutral communication tone, simple analysis requests, follow-up questions, critical thinking and the use of theoretical insights to formulate an enquiry. On the other end of the scale, the least prevalent code categories, in ascendent order are: praising tone and factual enquiries, declarative statements, questions about future scenarios, or collaborative-style question formulation.

Networks

The co-occurrence network (Figure 6) reveals a complex structure of interrelated codes, highlighting clusters of concepts that tend to appear together. For instance, codes related to critical thinking, simple analysis, and neutral tone formed a densely connected subnetwork, suggesting a pattern of reflective engagement. In contrast, codes such as passive consumption and basic facts appeared more peripherally, indicating more isolated or context-specific usage.

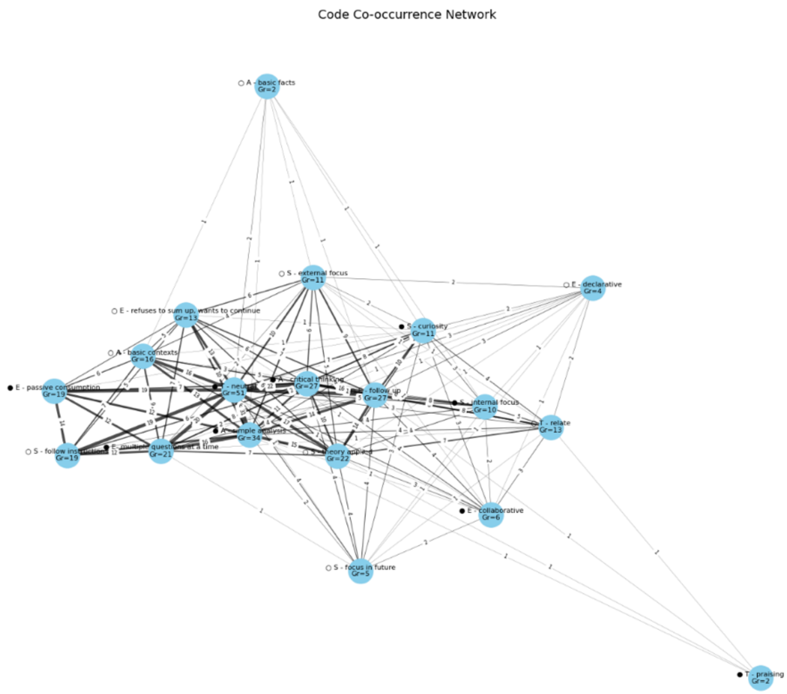

Figure 6- Co-occurrence network.

The code co-occurrence network analysis provided a visual and structural representation of how thematic codes were interrelated across the dataset. The network revealed a dense pattern of co-activation among several cognitive and interactional codes, particularly those associated with "A- critical thinking", "A – simple analysis", and "T – neutral tone". This suggests that participants frequently engage in reflective reasoning while maintaining an objective communicative stance. In contrast, codes such as "E – passive consumption" and "A – basic facts" appeared more peripheral, indicating more isolated or context-specific usage. These findings point to the presence of distinct engagement styles, with some participants demonstrating multidimensional cognitive processing, while others relied on more factual or passive responses. The network structure thus not only supports the identification of emergent thematic clusters but also offers insight into the complexity and variability of user engagement patterns in response to prompts.

The co-occurrence network analysis revealed key patterns in the relationships between codes derived from the dataset. The network consisted of nodes representing individual codes and edges indicating the frequency with which these codes co-occurred in the same context.

The most central code in the network was “T – neutral”, with a total of 197 co-occurrences, followed by “A - simple analysis” (147), “E - follow up” (125), “A - critical thinking” (123), and “S - theory applied” (102). These codes formed the core of the network, suggesting their prominence across participant responses. The strongest co-occurring code pairs included:

- “A - simple analysis” and “T – neutral” (31 co-occurrences)
- “A - critical thinking” and “T – neutral” (22)
- “E - follow up” and “T – neutral” (20)
- “E - multiple questions at a time” and “T – neutral” (20)
- “E - passive consumption” and “T – neutral” (19)

These frequent pairings indicate strong thematic links, particularly between analytical or exploratory behaviors and a neutral tone. Conversely, peripheral codes such as “T – praising” (4), “A - basic facts” (7), and “E – declarative” (19) showed limited co-occurrence, suggesting they were either context-specific or less emphasized in the data.

DISCUSSION AND CONCLUSIONS

This study was motivated by the growing integration of AI chatbots in higher education and the need to understand how students engage with these tools during cognitively demanding tasks. While prior research has focused on perceptions and outcomes, this study provides a granular analysis of actual student–AI interactions, addressing a critical gap in the literature. By examining emotional tone, communication style, and inquiry complexity, the study demonstrates that student engagement with AI tutors is not only a function of task complexity or technological familiarity but is also closely tied to emotional tone and communication style. Students who adopted a relational discourse (collaborative engagement, follow-up questioning) evidenced greater strategic inquiry and critical thinking. This finding is supported by recent studies in AI-supported learning (Al-Abdullatif & Alsubaie, 2024).

In depth analysis of student-AI synchronous communication can provide essential teaching and learning insights to better implement the use of AI chatbots in HE classrooms. Thematic and co-occurrence analyses revealed that students who adopted a relational tone and engaged in follow-up questioning demonstrated higher levels of critical thinking and strategic inquiry. Neutral tones were most prevalent but often accompanied by simpler analytical tasks. The co-occurrence network highlighted central codes such as “T – neutral,” “A – simple analysis,” and “E – follow up,” indicating their prominence in student discourse. These findings suggest that emotional tone and communication style are closely linked to the depth of cognitive engagement in AI-supported learning. The centrality of “T – neutral” across multiple code pairings suggests that a neutral tone was a common backdrop for various cognitive and behavioral expressions, including simple analysis, critical thinking, and follow-up behaviors. The predominance of neutral tones suggests a baseline approach whereby students interact with AI chatbots in an objective, factual manner. Yet, when socioaffective elements are present, cognitive engagement deepens, consistent with Kirk et al. (2025). This supports the hypothesis, grounded on VAM, that perceived value and emotional alignment with AI tools drive meaningful engagement and higher learning outcomes.

IMPLICATIONS

The findings contribute to theory by extending the Value-based Adoption Model (VAM) to the context of AI-assisted learning, highlighting the role of socioaffective alignment in technology adoption. Practically, the study informs educators and instructional designers about the importance of fostering relational engagement with AI tools to promote deeper cognitive processing. It also offers actionable insights for developing AI-integrated pedagogical strategies that enhance student agency, critical thinking, and strategic reasoning.

While the study offers rich qualitative insights, the study’s scope is limited by its small sample size (n=10) and focus on a business strategy task. The use of a single AI chatbot and the voluntary nature of student participation may also influence the generalizability of the findings. Additionally, the coding process, although validated, may reflect interpretive biases inherent in qualitative research.

Future studies should consider larger, more diverse samples and explore longitudinal effects of AI engagement on learning outcomes. Future research could explore how different types of AI prompts influence student engagement across disciplines and educational levels. Investigating the long-term impact of relational versus transactional AI interactions on skill development and academic performance would be valuable. Moreover, integrating multimodal data (e.g., voice, emotion detection) could enrich understanding of socioaffective dynamics. Finally, comparative studies across AI platforms and instructional designs could help refine best practices for AI integration in higher education.

REFERENCES

Al-Abdullatif, A. M., & Alsubaie, M. A. (2024). ChatGPT in Learning: Assessing Students' Use Intentions through the Lens of Perceived Value and the Influence of AI Literacy. *Behavioral Sciences*, *14*(9), 845. https://doi.org/10.3390/bs14090845

Ayanwale, M. A., & Molefi, R. R. (2024). Exploring intention of undergraduate students to embrace chatbots: From the vantage point of Lesotho. *International Journal of Educational Technology in Higher Education*, *21*(1), 20. https://doi.org/10.1186/s41239-024-00451-8

Bibbi, Z., & Atta, A. (2024). The Role of ChatGPT as AI English Writing Assistant: A Study of Student's Perceptions, Experiences, and Satisfaction. *Annals of Human and Social Sciences*, *5*(I). https://doi.org/10.35484/ahss.2024(5-I)39

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Ding, L., Li, T., Jiang, S., & Gapud, A. (2023). Students' perceptions of using ChatGPT in a physics class as a virtual tutor. *International Journal of Educational Technology in Higher Education*, *20*(1), 63. https://doi.org/10.1186/s41239-023-00434-1

Ghemawat, P. (2001). Distance still matters. The hard reality of global expansion. *Harvard Business Review*, *79*(8), 137–140.

Gill, S. S., Xu, M., Patros, P., Wu, H., Kaur, R., Kaur, K., Fuller, S., Singh, M., Arora, P., Parlikad, A. K., Stankovski, V., Abraham, A., Ghosh, S. K., Lutfiyya, H., Kanhere, S. S., Bahsoon, R., Rana, O., Dustdar, S., Sakellariou, R., … Buyya, R. (2024). Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots. *Internet of Things and Cyber-Physical Systems*, *4*, 19–23. https://doi.org/10.1016/j.iotcps.2023.06.002

González-González, C. S. (2023). El impacto de la inteligencia artificial en la educación: Transformación de la forma de enseñar y de aprender. *Qurriculum. Revista de Teoría,Investigación y Práctica Educativa*, *36*, 51–60. https://doi.org/10.25145/j.qurricul.2023.36.03

Kim, H.-W., Chan, H. C., & Gupta, S. (2007). Value-based Adoption of Mobile Internet: An empirical investigation. *Decision Support Systems*, *43*(1), 111–126. https://doi.org/10.1016/j.dss.2005.05.009

Kim, Y.-J., Cho, J., & Kang, S.-W. (2020). Study on the Relationship between Leisure Activity Participation and Wearing a Mask among Koreans during COVID-19 Crisis: Using TPB Model. *International*

Journal of Environmental Research and Public Health*, *17*(20), 7674. https://doi.org/10.3390/ijerph17207674

Kirk, H. R., Gabriel, I., Summerfield, C., Vidgen, B., & Hale, S. A. (2025). Why human–AI relationships need socioaffective alignment. *Humanities and Social Sciences Communications*, *12*(1), 728. https://doi.org/10.1057/s41599-025-04532-5

Kohnke, L., Moorhouse, B. L., & Zou, D. (2023). ChatGPT for Language Teaching and Learning. *RELC Journal*, *54*(2), 537–550. https://doi.org/10.1177/00336882231162868

Kosmyna, N., Hauptmann, E., Yuan, Y. T., & Situ, J. (2025). *Your Brain on ChatGPT: Accumulation of Cognitive Debt when Using an AI Assistant for Essay Writing Task*.

Liao, G., Li, M., Yin, J., & Wang, Q. (2022). Electronic communication during nonwork time and withdrawal behavior: An analysis of employee cognition-emotion-behavior framework from Chinese cultural context. *Frontiers in Psychology*, *13*, 1010197. https://doi.org/10.3389/fpsyg.2022.1010197

Martins, L., Fernández-Ferrer, M., & Puertas, E. (2024). Analysing Conversation Pathways with a Chatbot Tutor to Enhance Self-Regulation in Higher Education. *Education Sciences*, *14*(6), 590. https://doi.org/10.3390/educsci14060590

Mollick, E., & Mollick, L. (2024, October 31). Stop Writing All Your AI Prompts from Scratch. *Harvard Business Publishing Education*. https://hbsp.harvard.edu/inspiring-minds/an-ai-prompting-template-for-teaching-tasks

Nasni Naseri, R. N., & Abdullah, M. S. (2024). Understanding AI Technology Adoption in Educational Settings: A Review of Theoretical Frameworks and their Applications. *Information Management and Business Review*, *16*(3(I)), 174–181. https://doi.org/10.22610/imbr.v16i3(I).3963

Nguyen, A., Hong, Y., Dang, B., & Huang, X. (2024). Human-AI collaboration patterns in AI-assisted academic writing. *Studies in Higher Education*, *49*(5), 847–864. https://doi.org/10.1080/03075079.2024.2323593

Passonneau, S., & Coffey, D. (2011a). The Role of Synchronous Virtual Reference in Teaching and Learning: A Grounded Theory Analysis of Instant Messaging Transcripts. *College & Research Libraries*, *72*(3), 276–295. https://doi.org/10.5860/crl-102rl

Passonneau, S., & Coffey, D. (2011b). The Role of Synchronous Virtual Reference in Teaching and Learning: A Grounded Theory Analysis of Instant Messaging Transcripts. *College & Research Libraries*, *72*(3), 276–295. https://doi.org/10.5860/crl-102rl

Paulus, T., Woods, M., Atkins, D. P., & Macklin, R. (2017a). The discourse of QDAS: Reporting practices of ATLAS.ti and NVivo users with implications for best practices. *International Journal of Social Research Methodology*, *20*(1), 35–47. https://doi.org/10.1080/13645579.2015.1102454

Paulus, T., Woods, M., Atkins, D. P., & Macklin, R. (2017b). The discourse of QDAS: Reporting practices of ATLAS.ti and NVivo users with implications for best practices. *International Journal of Social Research Methodology*, *20*(1), 35–47. https://doi.org/10.1080/13645579.2015.1102454

Rahman, M. K., Ismail, N. A., Hossain, M. A., & Hossen, M. S. (2025). Students' mindset to adopt AI chatbots for effectiveness of online learning in higher education. *Future Business Journal*, *11*(1), 30. https://doi.org/10.1186/s43093-025-00459-0

Rapp, A., Curti, L., & Boldi, A. (2021). The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots. *International Journal of Human-Computer Studies*, *151*, 102630. https://doi.org/10.1016/j.ijhcs.2021.102630

Rruplli, E., Frydenberg, M., Patterson, A., & Mentzer, K. (2024). EXAMINING FACTORS OF STUDENT AI ADOPTION THROUGH THE VALUE-BASED ADOPTION MODEL. *Issues In Information Systems*, *25*(3), 218–230. https://doi.org/10.48009/3_iis_2024_117

Strzelecki, A. (2024). Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology. *Innovative Higher Education*, *49*(2), 223–245. https://doi.org/10.1007/s10755-023-09686-1

Sulatko, S. (2024). *Integrating Qualitative Content and Narrative Analysis: A Five-Step Approach*. Academic Conferences International Limited.

Thimmanayakanapalya, S. S., Mulgund, P., & Sharman, R. (2025). *A Discourse Structural Analysis Survey and Taxonomy for Chatbots*. *17*.

UNESCO. (2024). *AI competency framework for students*. UNESCO. https://doi.org/10.54675/JKJB9835

Usher, M., & Amzalag, M. (2025). From Prompt to Polished: Exploring Student–Chatbot Interactions for Academic Writing Assistance. *Education Sciences*, *15*(3), 329. https://doi.org/10.3390/educsci15030329

Villegas-Ch, W., Arias-Navarrete, A., & Palacios-Pacheco, X. (2020). Proposal of an Architecture for the Integration of a Chatbot with Artificial Intelligence in a Smart Campus for the Improvement of

Learning. *Sustainability*, *12*(4), 1500. https://doi.org/10.3390/su12041500
Walter, Y. (2024). Embracing the future of Artificial Intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, *21*(1). https://doi.org/10.1186/s41239-024-00448-3
Wang, C., Wang, H., Li, Y., Dai, J., Gu, X., & Yu, T. (2025). Factors Influencing University Students' Behavioral Intention to Use Generative Artificial Intelligence: Integrating the Theory of Planned Behavior and AI Literacy. *International Journal of Human–Computer Interaction*, *41*(11), 6649–6671. https://doi.org/10.1080/10447318.2024.2383033
Yu, J., Lee, H., Ha, I., & Zo, H. (2017). User acceptance of media tablets: An empirical examination of perceived value. *Telematics and Informatics*, *34*(4), 206–223. https://doi.org/10.1016/j.tele.2015.11.004
Zhao, Z., An, Q., & Liu, J. (2025). Exploring AI tool adoption in higher education: Evidence from a PLS-SEM model integrating multimodal literacy, self-efficacy, and university support. *Frontiers in Psychology*, *16*, 1619391. https://doi.org/10.3389/fpsyg.2025.1619391

Maribel Labrado-Antolín, PhD, is an Associate Professor in the School of Business and Economics, Complutense University of Madrid. Her major research interests include new approaches to work, human resource management, higher education, and talent development. Email: mlabra02@ucm.es

Note: The author would like to acknowledge the use of OpenAI's ChatGPT in refining language. The AI tool provided support in editing and formatting the manuscript. All ideas and interpretations are the original work of the author. The contributions made by ChatGPT helped enhance the overall quality of this work.