Check for updates

Received: 28 November 2024 | Accepted: 30 March 2025

DOI: 10.1111/bjet.13588

ORIGINAL ARTICLE

British Journal of Educational Technology BERA

Analysing nontraditional students' ChatGPT interaction, engagement, self-efficacy and performance: A mixed-methods approach

Mohan Yang[1] | **Shiyan Jiang**[2] | **Belle Li**[3] | **Kristin Herman**[4] | **Tian Luo**[4] | **Shanan Chappell Moots**[5] | **Nolan Lovett**[6]

[1]Educational Administration and Human Resource Development, Texas A&M University, College Station, Texas, USA

[2]Teacher Education and Learning Sciences, North Carolina State University, Raleigh, North Carolina, USA

[3]Curriculum and Instruction, Purdue University, West Lafayette, Indiana, USA

[4]Department of STEM Education and Professional Studies, Old Dominion University, Norfolk, Virginia, USA

[5]The Center for Educational Partnerships, Old Dominion University, Norfolk, Virginia, USA

[6]Department of Educational Leadership and Workforce Development, Old Dominion University, Norfolk, Virginia, USA

Correspondence
Mohan Yang, Texas A&M University, EDCT 559, 540 Ross Street, College Station, TX 77843, USA.
Email: mohanyang@tamu.edu

Generative artificial intelligence brings opportunities and unique challenges to nontraditional higher education students, stemming, in part, from the experience of the digital divide. Providing access and practice is critical to bridge this divide and equip students with needed digital competencies. This mixed-methods study investigated how nontraditional higher education students interact with ChatGPT in multiple courses and examined relationships between ChatGPT interactions, engagement, self-efficacy and performance. Data were collected from 73 undergraduate and graduate students through chat logs, course reflections and artefacts, surveys and interviews. ChatGPT interactions were analysed using four metrics: prompt number, depth of knowledge (DoK), prompt relevance and originality. Results showed that ChatGPT prompt numbers ($\beta = 0.256$, $p < 0.03$) and engagement ($\beta = 0.267$, $p < 0.05$) significantly predicted performance, while self-efficacy did not. Students' DoK ($r = 0.40$, $p < 0.01$) and prompt relevance ($r = 0.42$, $p < 0.01$) were positively correlated with performance. Text mining analysis identified distinct interaction patterns, with 'strategic inquirers' demonstrating significantly higher performance than 'exploratory inquirers' through more sophisticated follow-up questioning. Qualitative findings revealed that while most students were first-time ChatGPT users who initially showed resistance, they developed

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.
© 2025 The Author(s). *British Journal of Educational Technology* published by John Wiley & Sons Ltd on behalf of British Educational Research Association.

growing acceptance. Still, students tended to use ChatGPT sparingly and, even then, as only a starting point for assignments. The study highlights the need for targeted guidance in prompt engineering and AI literacy training to help nontraditional higher education students leverage ChatGPT more effectively for higher-order thinking tasks.

KEYWORDS
ChatGPT, depth of knowledge, engagement, generative AI, nontraditional students, performance, self-efficacy

Practitioner notes

What is already known about this topic

- Nontraditional students face unique challenges in higher education, such as limited technological literacy and digital access.
- The emergence of generative AI tools presents both opportunities and challenges for addressing educational disparities.
- Existing studies on AI implementation predominantly focus on traditional students.

What this paper adds

- Empirical evidence of how nontraditional students interact with ChatGPT through multiple metrics (prompt number, DoK, relevance and originality).
- Distinct interaction patterns and their relationship to performance outcomes.
- The relationship among ChatGPT interactions, engagement, self-efficacy and performance.

Implications for practice and/or policy

- Need for explicit instruction in prompt engineering as a critical skill for higher-order thinking.
- Importance of providing targeted technology training and self-paced learning resources for nontraditional students.
- Value of developing comprehensive AI literacy training that addresses both tool capabilities and limitations.

INTRODUCTION

The landscape of higher education is undergoing a dramatic transformation driven by two concurrent trends: the growing presence of nontraditional students (Dolch & Zawacki-Richter, 2018) and the rapid emergence of artificial intelligence (AI) tools, particularly generative AI (GenAI) technologies (Bolick & da Silva, 2024; Yan et al., 2024). When taken together, they present a unique opportunity for the field to centre both opportunities and challenges around this rapid advancement, promoting the equitable design, implementation and use of

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

AI within higher education. Equitable human–AI partnerships require that humans of varied backgrounds and identities are included in the design and deployment of the technologies, have agency during the use of the technologies and see positive outcomes that meet their individual and community goals as they use the technologies for learning and life.

Providing equal access to and increasing the diversity of the student body to reflect population diversity have been initiatives in higher education (Holmegaard et al., 2017). Nontraditional students constitute a significant portion of the higher education population, with enrolment continuing to rise even as other subpopulations have remained stable or declined (Dolch & Zawacki-Richter, 2018). Among prime-age adults (25–54), approximately 61 million of them without a bachelor's degree were in the labour force in the United States in 2021, and roughly 4.3 million adults were enrolled in postsecondary education in the same year (Bauer et al., 2023), indicating a critical gap in expanding higher education access. Nontraditional students are typically defined in the United States as those who are older than 24, employed full-time, financially independent or have dependents (Bean & Metzner, 1985; Choy, 2002; Cleveland-Innes, 1994; Jones & Watson, 1990). In some European countries, however, nontraditional students can refer to those from underrepresented groups, such as minority or low socio-economic backgrounds (Holmegaard et al., 2017; Sapir, 2022). Importantly, unlike traditional students, these demographics often intersect in ways that require complex balancing acts for students simultaneously managing academic, professional and personal lives (Markle, 2015). These students often face unique challenges, including limited technological literacy and access to digital resources, creating a persistent digital divide that can impede their academic success (Banerjee, 2020). Mere digital access is not sufficient (Fairlie & London, 2012). Targeted support and training to empower nontraditional students in bridging the digital divide are necessary (Jesnek, 2012).

The advent of AI tools, particularly ChatGPT, presents both opportunities and challenges for addressing these educational disparities. While these technologies offer potential benefits, such as personalized learning support and automated feedback, they also risk widening the existing digital divide if not thoughtfully implemented. Exposing nontraditional students to AI tools could help bridge this gap by providing accessible technological support for their learning needs (Banerjee, 2020). However, understanding how these students interact with such tools and the subsequent impact on their learning outcomes remains crucial for curriculum design, effective implementation to develop their digital literacy, a critical skill in today's workforce. Yet, extant research on digital technology usage, especially GenAI tools, primarily focuses on traditional students, leaving a gap in understanding how nontraditional students interact with these technologies. While existing studies have shed light on the digital exclusion faced by underrepresented students (Kuo, 2018), exploring how AI can be leveraged to contribute to student empowerment is a more strengths-based approach to examining the interactions of marginalized learners. Learner agency is intentionally centred (Sulecio de Alvarez & Dickson-Deane, 2018), reconceptualizing human–AI interaction as transformative instead of transactional (Lombard, 2022).

Despite the growing adoption of AI in education, several critical gaps persist in our understanding. First, there is limited empirical evidence regarding the impact of these tools on learning and instructional design processes, particularly for nontraditional students. We lack comprehensive metrics for evaluating learner-AI interactions, making it difficult to assess the effectiveness of these tools in supporting student learning. Third, the intricacies of human–AI interaction patterns among students remain poorly understood. These gaps hinder our ability to support nontraditional learners in navigating 'jagged technological frontier' (Dell'Acqua et al., 2023). In responding to these gaps, we adopted GenAI tools in the target courses within which the majority of students identified themselves as nontraditional students. Through 2023 and 2024, we integrated GenAI tools, such as ChatGPT in multiple instructional design and human resource development courses to help students explore the

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

technological integration in learning and design process as an effort for developing their digital awareness and competencies. The purpose of this study is to address the mentioned gaps by examining how nontraditional undergraduate and graduate students interact with ChatGPT and the relationships among their ChatGPT interaction, engagement, self-efficacy and performance for a holistic picture of students' ChatGPT interaction. Specifically, we evaluate their interactions through multiple metrics, including the number of prompts, depth of knowledge in questioning, prompt relevance and evolution, and originality. By analysing these interactions and their impact on students' instructional design and writing performance, we aim to develop a more nuanced understanding of how GenAI tools can be effectively leveraged to support nontraditional students' academic success.

LITERATURE REVIEW

Nontraditional learners in the AI age

Nontraditional students differ from the conventional undergraduate archetype—18–22 year-old, full-time enrolled, parent-dependent students pursuing immediate postsecondary education. Bean and Metzner's (1985) foundational framework emphasizes age (>24), non-residential status and part-time enrolment as primary identifiers, which was expanded with new identifiers added including first-generation status and non-standard high school credentials (The National Postsecondary Student Aid Study, 1999) and delayed enrolment, employment, financial independence and caretaking responsibilities (Horn et al., 2006). Increasingly, nontraditional populations are seeking career advancement or personal enrichment (Cavazos et al., 2024; Dolch & Zawacki-Richter, 2018; Shepherd & Sheu, 2014). Yet, the complex time management in balancing academic, professional and personal responsibilities poses challenges for these students (Markle, 2015).

In supporting nontraditional students' needs, AI applications in higher education span four main areas: profiling and prediction, intelligent tutoring systems, assessment and evaluation, and adaptive systems and personalization (Zawacki-Richter et al., 2019). In instructional design specifically, Bolick and da Silva (2024) highlighted how AI tools can enhance workflows through content creation, outlining, storyboarding, scenario generation and personalization. For nontraditional students, these AI-assisted capabilities could significantly streamline their workflow, allowing focus on higher-order aspects of design. However, effectively leveraging these tools requires navigating the 'jagged technological frontier', where AI capabilities vary significantly across tasks. Understanding these human–AI interaction styles is crucial for supporting nontraditional students, particularly given the digital divide that encompasses not just technology access but also the skills required to use it effectively (Banerjee, 2020).

Large language models (LLM) in education

The complexity of AI integration is particularly evident in LLMs interactions. While Kumar et al. (2024) found that GenAI assistance can build system trust and improve performance, Zamfirescu-Pereira et al. (2023) revealed significant challenges non-experts face in prompt design, including over-generalization and misapplied interaction expectations, potentially exacerbating rather than alleviating nontraditional students' educational barriers. Dell'Acqua et al. (2023) identified two successful AI use patterns: 'Centaurs', who strategically delegate tasks, and 'Cyborgs', who deeply integrate AI into their workflow. Similarly, Nguyen et al. (2024) found that 'Structured Adaptivity' approaches yield better outcomes than 'Unstructured Streamline' methods. However, achieving these optimal interaction patterns

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13580 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

requires specific guidance and support that many nontraditional students may lack. While example-based instruction (Wittwer & Renkl, 2010) and metacognitive strategies (Alt & Raichel, 2020) show potential for supporting AI tool use, understanding how to effectively adapt these approaches for nontraditional students requires dedicated research.

Studies have also examined prompt frequency and complexity (White et al., 2023). The Human-AI Language-based Interaction Evaluation (HALIE) framework evaluates human-LLM interaction across three dimensions: targets (process vs. output), perspectives (first-person vs. third-party) and criteria (quality vs. preference; Lee et al., 2023). HALIE was validated across diverse tasks, demonstrating that interaction-based evaluation can reveal insights not captured by traditional non-interactive benchmarks.

Student engagement with educational technology encompasses behavioural, emotional and cognitive dimensions (Fredricks & McColskey, 2012; Henrie et al., 2015). In the context of LLM interaction, emotional engagement reflects students' affective reactions, including interest, enjoyment and anxiety when using AI tools (Uddin et al., 2023). Behavioural engagement manifests through observable participation patterns, such as the frequency and consistency of LLM use (Lo et al., 2024), while cognitive engagement involves the psychological investment in learning and self-regulation strategies (Escalante et al., 2023; Zhang & Tur, 2023). HALIE, similarly, delineates engagement into emotional dimensions (student confidence and comfort in AI tool usage), cognitive aspects (depth of understanding and learning strategy development) and behavioural patterns (interaction frequency and consistency). The relationship between these engagement patterns and learning outcomes remains particularly unexplored for nontraditional students, despite evidence suggesting that interaction quality may be more important than quantity for learning outcomes (Lee et al., 2023).

Depth of knowledge and prompt relevance

Webb's Depth of Knowledge (DoK; Webb, 2002) analyses learning activities complexity and guides educators in designing assessments (Harris & Patten, 2015; Hess et al., 2009), developing learning activities (Barber, 2018; Francis, 2021) and aligning curriculum with learning objectives (Traynor et al., 2020; Wyse & Viger, 2011) including curriculum designed specifically for neurodivergent learners (Morgan et al., 2014). Its applications now extend to analysing learner engagement with AI systems, where prompts reflect the cognitive complexity of student interactions with AI systems. The sophistication of prompts can range from basic information retrieval to complex analytical queries, indicating different levels of cognitive processing and understanding (see Figure 1 and Appendix A).

Prompt relevance measures how effectively students' queries relate to and build upon each other. Li et al. (2024) found that successful learners craft sequences of interconnected

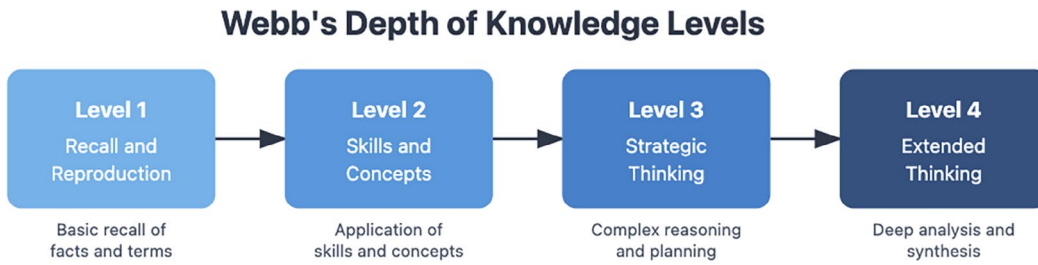


FIGURE 1 Webb's DOK levels.

prompts that progressively develop their understanding. Prompt evolution examines how students' interaction patterns with AI systems change over time. Students who progressively refine their prompts show deeper engagement with the material and better learning outcomes (Chang et al., 2023). This evolutionary process often involves students moving from simple, direct questions to more nuanced and contextual queries that demonstrate increasing mastery of both the subject matter and the AI tool itself.

RESEARCH QUESTIONS

To bridge the gaps as mentioned above, we seek to explore students' ChatGPT interactions, engagement, self-efficacy and performance with the following guiding research questions (RQ):

1. How did students perform in interacting with ChatGPT to facilitate their learning and design process?
2. How were students' ChatGPT interactions, engagement, self-efficacy and learning performance related to each other?
3. What were students' experiences in using ChatGPT to facilitate their learning and design?

METHODOLOGY

Research design

To answer the research questions, we conducted a sequential explanatory mixed-methods study (Creswell & Clark, 2017) with text mining techniques applied to extract the patterns of students' ChatGPT interaction (see Figure 2).

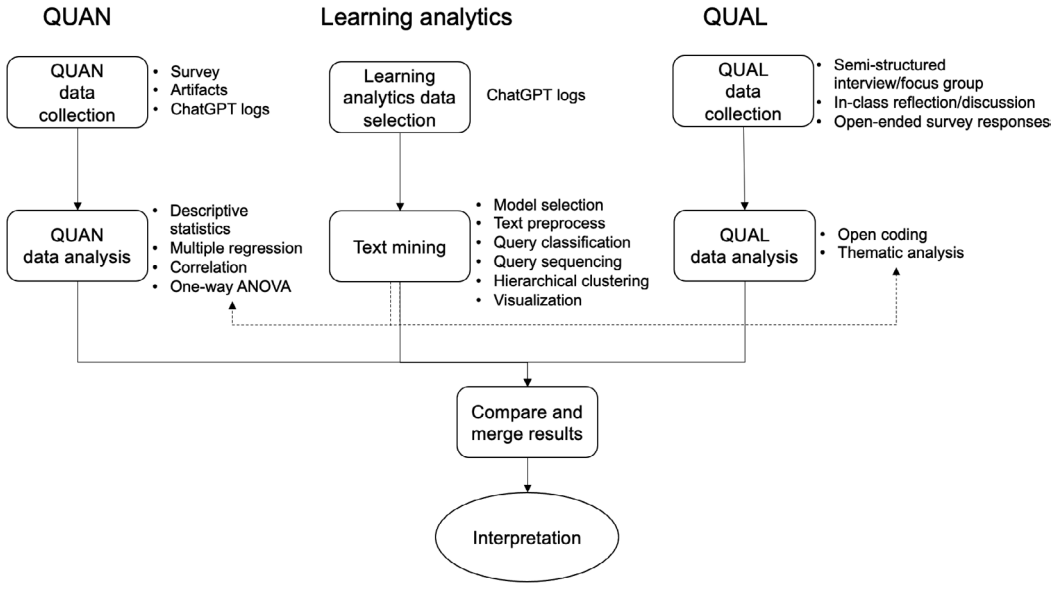


FIGURE 2 Study process.

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Context and participants

This study was conducted at a mid-Atlantic, research-intensive, minority-serving public university in the United States. Approximately 38% of students are from underrepresented ethnic groups, over half of the undergraduate students receive financial aid, one-third of students are enrolled part-time, and approximately one-third of freshmen are first-generation students. From 2023 to 2024, GenAI was integrated into instructional design projects in two undergraduate and one graduate course with a total of 75 students in the areas of technology, instructional design and human resource development. According to students' demographic information, between 78% and 80% of students (missing data from five students) in those classes were nontraditional students that met at least one of the characteristics of the traditional definition, such as age, job or parenting. When underrepresented students were considered as nontraditional students as well, the rate could reach approximately 90% or higher based on students' demographics, but we were unable to verify the specific number for this study due to missing data. Prior to course activities, students were supported with a ChatGPT guide and video demos. Data collection included end-of-course surveys yielding 73 complete matched projects for quantitative analysis and 82 projects/chat logs for text mining analysis.

Data collection

Data were collected at multiple stages and from multiple sources (see Table 1).

TABLE 1 Data sources.

Data sources	Description	RQs
ChatGPT logs	As part of the assignments, all students were required to use ChatGPT towards their designs following specific instructions (eg, when and how to use ChatGPT). During classes, students needed to record their' interaction with ChatGPT are recorded and submit it including their prompts and ChatGPT outputs and submit it either as a link or document along with their projects. For the purposes of the course assignments, the grade of ChatGPT interactions was weighted equally with the designed project to ensure students' effort in using the tool	1 & 2
Class artefacts	During classes, students submitted their design or writings that were completed with the facilitation of ChatGPT. Artefacts were examined and evaluated along with their ChatGPT interactions	2
Reflection & discussion	Students reflected on their usage of ChatGPT and discussed the role of technology at different points of the courses. Reflection or discussion prompts were provided	2 & 3
Survey	A one-time postsurvey on students' perceived self-efficacy and engagement was conducted following a 5-Likert scale at the end of the semester. Open-ended questions were also added to collect students' experience and insights of using the tool in the courses	2
Interview/focus group	A group of four students from each class was formed for a focus group focusing on their experience using ChatGPT. Two individual interviews were conducted in one of the courses due to scheduling challenges. Each interview/focus group lasted approximately 60 minutes	1, 2, & 3

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Research variables and measurement

We adapted HALIE (Lee et al., 2023) as our theoretical framework to guide the development of our metrics in evaluating students' ChatGPT interactions (see Figure 3). While originally designed for evaluating language models, HALIE's structure and focus on interaction processes, targets (process vs. output), perspectives (first-person vs. third-party) and criteria (quality vs. preference) makes it equally valuable for studying user behaviour, adaptation patterns and experience. The framework provides researchers with a systematic methodology for collecting and analysing both quantitative and qualitative data about how users interact with AI systems over time. It aligns with our investigation of interaction characteristics, engagement patterns and performance indicators.

Table 2 illustrates how HALIE's three-dimensional structure guided our assessment development.

Learning performance

Students' performance was measured by evaluating their course project against corresponding pre-established rubrics. To avoid the potential bias from the course instructor, one co-author conducted the evaluation specifically for the research. All performance scores were converted into percentages first and then transformed into z scores to ensure suitability in the regression model.

ChatGPT interaction

In measuring ChatGPT interaction, four metrics as four separate variables were developed, including (1) prompt number, (2) the depth of knowledge, (3) the prompt relevance and evolution, and (4) the originality of work. Prompt number refers to the number of prompts for a corresponding project. Two authors independently examined all chat logs following

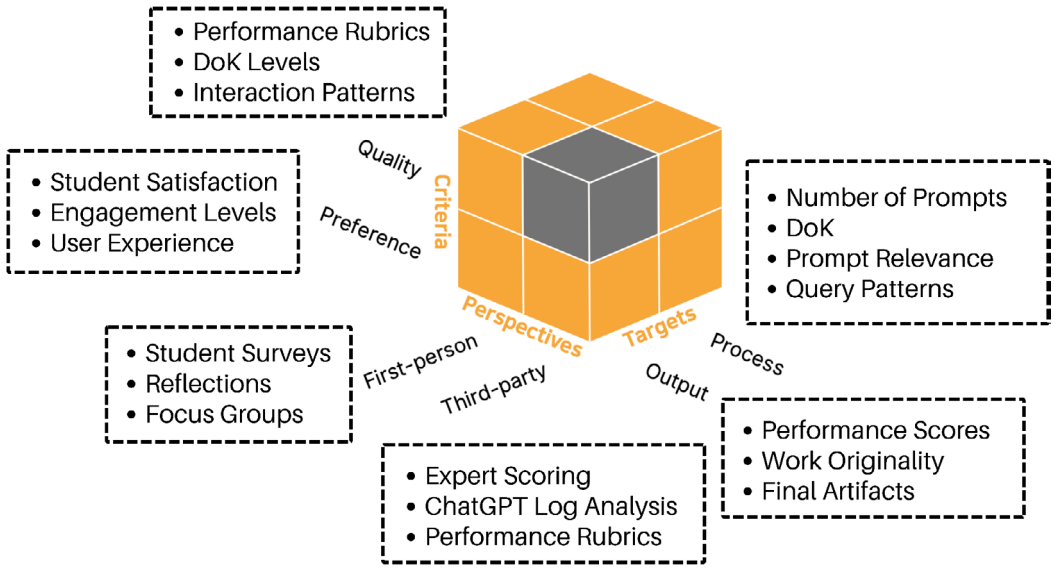


FIGURE 3 Research theoretical framework. *Source*: Adapted from Lee et al. (2023).

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13580 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 Mapping HALIE framework dimensions to assessment indicators.

HALIE dimension	Component	Assessment indicators	Measurement approach
Targets	Process	Prompt number	Count of student-initiated prompts per project
		Depth of Knowledge (DoK)	Four-level rubric assessing cognitive complexity
		Prompt relevance	Four-level rubric evaluating query progression
	Output	Originality	Four-level rubric measuring personal contribution
		Performance score	Rubric-based assessment by external evaluator
Perspectives	First-person	Self-efficacy	Five-item scale (Avey et al., 2009)
		Emotional engagement	Two-item scale (Skinner et al., 2009)
		Student reflections	Qualitative analysis of reflections/ discussions
	Third-party	Expert evaluation	Independent assessment by two researchers
		Interaction analysis	Text mining of query patterns
Criteria	Quality	DoK levels	Evaluation of cognitive engagement
		Prompt relevance	Assessment of strategic development
		Output originality	Evaluation of creative transformation
	Preference	Engagement measures	Combined emotional/cognitive/ behavioural scores
		User experience	Analysis of qualitative feedback

the DoK and prompt relevance metrics. A final score was assigned after consensus was reached for each project. DoK level indicates a student's cognitive engagement and reasoning in questioning ChatGPT, examined as part of the quality criteria. Analysing quality in human–AI interactions provides insight into students' cognitive engagement and learning development (Lee et al., 2023). The prompt relevance refers to how prompts are related and evolve as students interact with ChatGPT. As ChatGPT interaction is a required part of the project development, the work originality becomes an essential aspect of understanding the learning and design process, which was evaluated by comparing students' work and the ChatGPT logs. All metrics can be seen in Appendix A.

Self-efficacy

Self-efficacy of using ChatGPT was measured with items adapted from Avey et al. (2009). Overall, five items were used.

Engagement

Engagement has been measured from different perspectives in different contexts. We measured three dimensions, including emotional, cognitive and behavioural. We measured emotional engagement, a dimension that has not been addressed comprehensively in technology-enhanced learning (Halverson & Graham, 2019) with two items adapted from

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Skinner et al. (2009). Cognitive engagement focused on the perceived value, persistence and critical thinking effort (Fredricks et al., 2004; Halverson & Graham, 2019; Reschly & Christenson, 2012). Behavioural engagement measures students' participation and concentration with items adapted from Skinner et al. (2009). The engagement variable composite score calculated by summing students' self-reported scores on emotional, cognitive and behavioural engagement items.

Data analysis

Quantitative strand

A multiple regression analysis was conducted with performance as the dependent variable (DV) and prompt number, engagement and self-efficacy as the independent variables (IVs) to investigate their influence on students' ChatGPT-facilitated performance score. The DoK, prompt relevance and originality variables violated one or more assumptions of the multiple regression technique (eg, linearity and collinearity), so we opted instead to examine the relationships between these variables and performance using Pearson product moment correlations. Additionally, a correlation analysis was conducted among the ChatGPT interactions, engagement and self-efficacy.

Qualitative strand

The qualitative analysis involves both deductive and inductive coding and thematic analysis on semi-structured interview/focus group, students' in-class reflection/discussion and their responses to the open-ended survey questions. Two coders followed a deductive approach and coded the data independently, followed by meetings to finalize codes until a consensus was reached. A third coder followed an inductive approach independently. The codes were merged for reconfiguration and categorization.

Text mining strand

We employed a mixed-methods approach to analyse their query patterns and their relationship to performance. In this study, we use query and prompt interchangeably. Using the facebook/bart-large-mnli model, a state-of-the-art zero-shot classification model that is ideal for handling the diverse and naturally occurring queries generated by students (Champa et al., 2024), we classified the queries into five categories: Information Request (seeking specific factual answers), Clarification (resolving ambiguities), Explanation (understanding or reasoning), Follow-Up (expanding upon previous queries) and Query (broad or unspecific questions). The high semantic understanding of the model guaranteed accuracy in capturing the intent behind each student query. We then generated query sequences, representing the chronological progression of their interactions with ChatGPT (eg, Information Request and Clarification). These sequences captured the dynamic nature of student interactions and allowed for an analysis of their query progression patterns. Hierarchical clustering was applied to the query sequences to identify distinct interaction patterns (Jiang et al., 2021). A dendrogram analysis helped to determine the optimal cluster number, with each one representing a unique interaction strategy. We visualized the query clusters using D3.js for intuitive interpretation.

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

To examine the link between clusters and performance outcomes, we conducted a one-way ANOVA. We selected a representative student from each cluster based on prompt frequency, performance and students' reflection, to illustrate the query patterns for a more nuanced understanding of the differences. The thematic analysis on reflections (Clarke & Braun, 2017) provided additional insights and contextualized the interaction patterns and their impact on performance. This combined quantitative and qualitative approach offered a comprehensive understanding of how query behaviours influenced learning performance.

RESULTS

Quantitative strand

The descriptive statistics revealed that the mean performance score, DoK and prompt relevance mean scores were relatively low, while the originality had a higher mean score (see Table 3). The engagement and self-efficacy mean scores indicated that students were engaged in the projects and had a relatively high self-efficacy level.

A total of 73 cases had scores for all three variables and were included in the multiple regression analysis. The findings revealed that the three predictors provided a good model fit, explaining a statistically significant proportion of variance ($R^2 = 0.17$, $F = 4.70$ (3, 69), $p < 0.01$). Results indicated that prompt number and engagement were both statistically significant positive predictors of learning performance, but students' self-efficacy scores did not significantly influence performance (see Table 4).

Prior to examining correlations among participants' learning performance, number of prompts, DoK, prompt relevance, engagement, self-efficacy and originality scores, we examined distributions for these variables to determine normality. Skewness for each of the variables was within the acceptable range of ±1.00, so we proceeded with the Pearson correlation analyses. To account for multiple comparisons between learning performance, DoK, prompt relevance and originality, we used an adjusted p value of 0.02 (3 comparisons divided by 0.05), and to account for multiple comparisons between ChatGPT interaction variables, we used an adjusted p value of 0.003, calculated using the conservative Bonferroni approach (15 comparisons divided by 0.05). We found statistically significant positive correlations between learning performance and students' DoK ($r = 0.40$, $p < 0.02$) and prompt relevance ($r = 0.42$, $p < 0.02$), with a non-significant negative correlation observed between performance and originality ($r = -0.13$, $p = 0.26$). The findings of correlations between students' ChatGPT interactions are shown in Table 5. Prompt number is significantly correlated with DoK and prompt relevance. DoK is significantly correlated with prompt relevance. Originality is significantly negatively correlated with DoK, prompt relevance and

TABLE 3 Descriptive statistics for performance score and ChatGPT interaction variables.

	N	Minimum	Maximum	Mean	SD
Performance (original percentage score)	73	34.38	100.00	67.76	18.34
Standardized performance	73	−1.82	1.76	0.00	1.00
ChatGPT prompt number	73	1	34	7.03	7.04
Depth of knowledge	73	1	4	1.90	1.00
Prompt relevance	73	1	4	1.99	1.09
Originality	73	1	4	2.79	1.12
Engagement	73	9	35	27.77	6.12
Self-efficacy	73	10	25	20.30	3.33

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 4 Influence of interaction, engagement and self-efficacy of ChatGPT on performance.

Independent variable	Unstandardized coefficients			
	B	SE	*β*	*p*
ChatGPT prompt number	0.036	0.016	0.256	0.03
Engagement	0.044	0.021	0.267	0.05
Self-efficacy	0.026	0.039	0.086	0.51

TABLE 5 Correlations between ChatGPT interaction variables.

	Prompt number	DoK	Prompt relevance	Originality	Engagement	Self-efficacy
Prompt number	1					
DoK	0.747**	1				
Prompt relevance	0.738**	0.917**	1			
Originality	−0.204	−0.291	−0.277	1		
Engagement	−0.036	0.175	0.140	−0.192	1	
Self-efficacy	0.129	0.221	0.162	−0.237	0.531**	1

**Correlation is significant at the 0.003 level (2-tailed).

self-efficacy. Self-efficacy is significantly correlated with engagement. Figure 4 illustrated the relationships between the variables.

Text mining strand

Our analysis identified three distinct clusters of query patterns, highlighting diverse approaches to interacting with ChatGPT, with 11 students in Cluster 1, 16 students in Cluster 2 and 48 students in Cluster 3 (Figure 5). The additional seven students fell above the threshold defined by the horizontal line in the hierarchical clustering dendrogram and formed an outlier group. A one-way ANOVA revealed a significant difference in learning performance between at least two groups ($F(3, 78) = 3.451$, $p = 0.02$), with Tukey's HSD test showing a significantly different result between Clusters 1 and 3 ($p = 0.025$. 95% CI = 1.513, 31.93). Despite the different sample sizes between groups, the homogeneity of variance was not violated. Below, we described Clusters 1 and 3 in greater detail and used representative students to further demonstrate the differences.

Cluster 1: Strategic inquirers

Cluster 1 was characterized by structured and purposeful query sequences, often transitioning from such as Explanation to repeated Follow-Up queries (Figure 6, left). These 'strategic inquirers' adopted a deliberate approach to iteratively refine and expand their understanding by systematically building on previous responses. It also demonstrated their metacognitive awareness of their learning needs and a strategic use of ChatGPT to meet those needs. After obtaining initial information, they often posed follow-up questions to clarify nuances, requested additional context or probed deeper into the topic. This iterative engagement effectively created a dialogue with the AI, supporting their ability to construct deeper and more cohesive understandings. Furthermore, these students demonstrated a goal-oriented

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

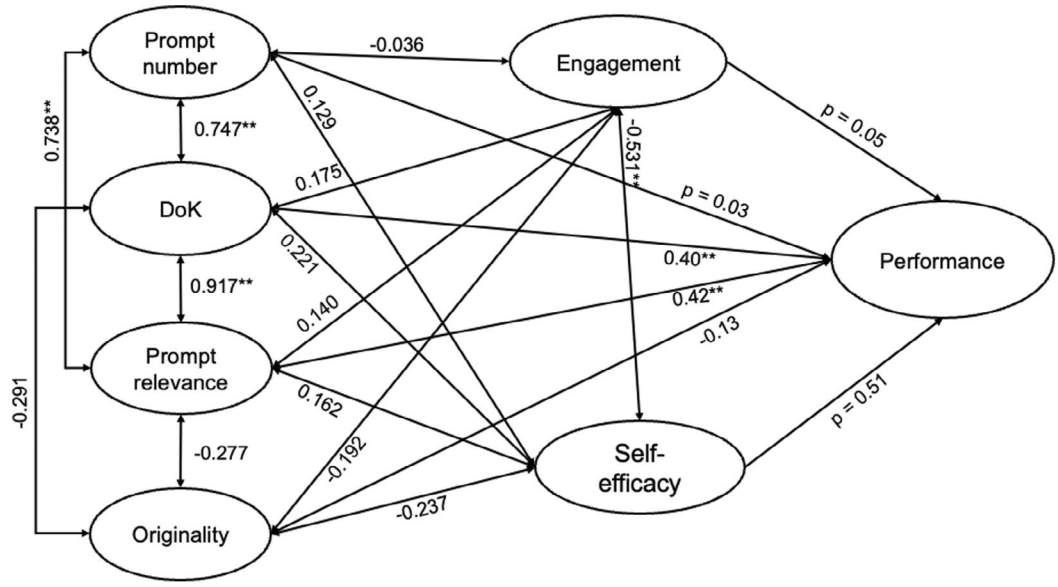


FIGURE 4 Relationships between the variables. ** Correlation is significant at the 0.003 level (2-tailed).

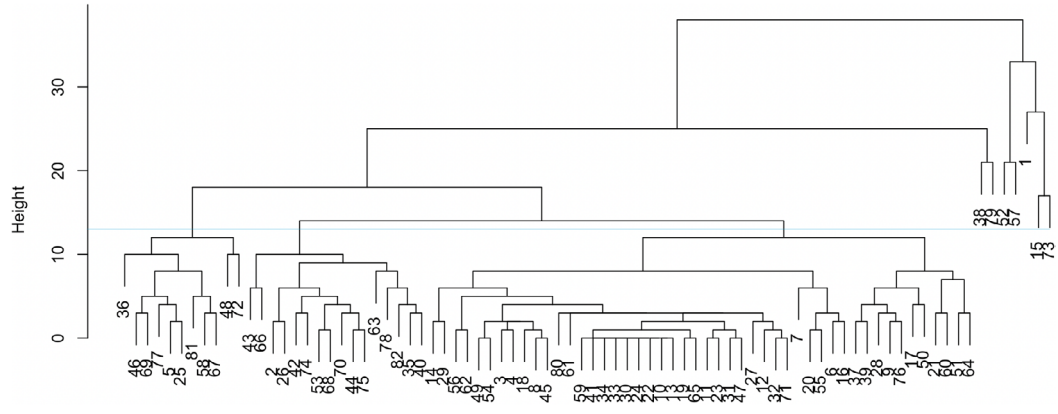


FIGURE 5 Hierarchical clustering dendrogram of student query patterns. The dendrogram visualizes the clustering of students based on the similarity of their query sequences when interacting with ChatGPT. Each number in the dendrogram represents a unique ID. The horizontal line indicates the threshold used to identify three distinct clusters.

manner, shaped by clear objectives. This behaviour aligns with theories of self-regulated learning, where learners actively monitored and adapted their strategies to achieve specific outcomes. The structured nature of their query sequences implied students' purposeful scaffolding learning processes, which could have contributed to better performance.

Tray (performance score: 100; 11 queries; DoK: 4; prompt relevance: 4; originality: 2; engagement: 32 out of 35; self-efficacy: 24 out of 25.) displayed a structured and purposeful approach to engaging with ChatGPT (Figure 6, right). He began with a broad Explanation query that established the overarching topic of interest for a more targeted exploration. Following this, Tray made an Information Request to gather foundational knowledge about the subject, anchoring the broader topic within a historical context. Building on this, Tray

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13580 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

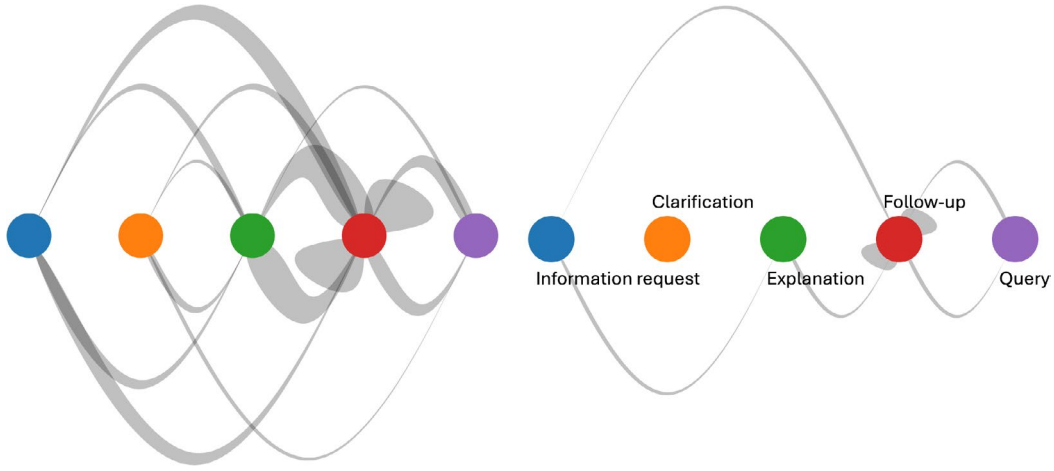


FIGURE 6 Visualization of query patterns for Cluster 1 (left) and Tray (pseudonym; right). Weighted arcs indicate the transition frequency. Top arcs represent left-to-right transitions, while bottom arcs are opposite.

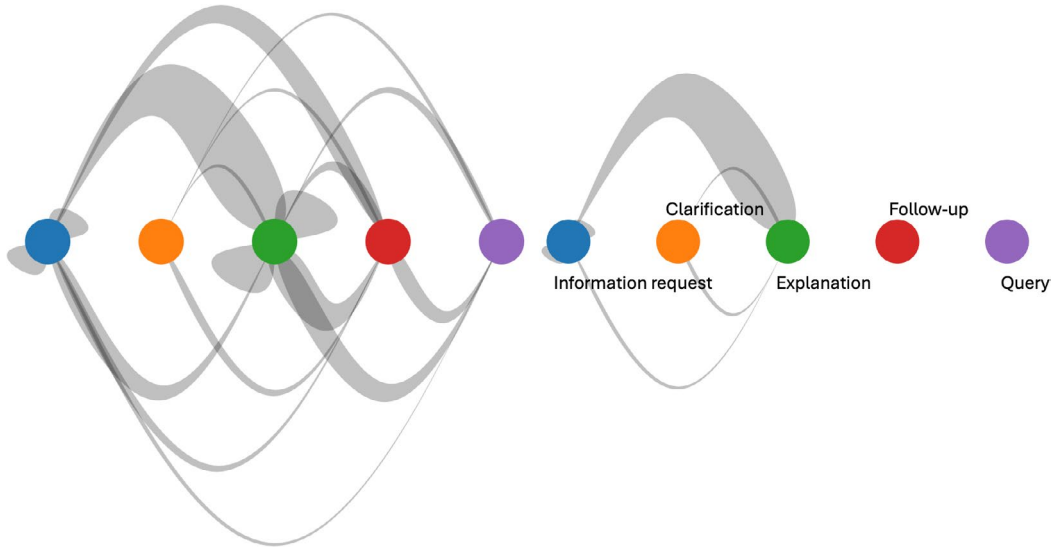


FIGURE 7 Visualization of query patterns for Cluster 3 (left) and Bella (pseudonym; right).

transitioned into a series of focused Follow-Up queries, signalling a clear goal to develop a comprehensive lesson plan. As the interaction progressed, Tray maintained focus and dived into detailed aspects (eg, reasonably priced materials and specific features of the target objects). Tray's query sequence reflected a strategic use of ChatGPT to scaffold learning objectives, systematically building a robust understanding of both the process of the topic and the educational framework for teaching it. The repeated Follow-Up queries revealed a metacognitive approach, with Tray refining goals and clarifying details to achieve a deeper understanding. This culminated in an Explanation query that synthesized prior insights into a format suitable for a specific instructional context. In the survey and reflection, Tray mentioned his experience with ChatGPT at his job and enjoyment using ChatGPT in this course.

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13580 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

To him, the best way is to 'act as if I am talking to another person and tell it exactly what I am looking for'. Even though he acknowledged that ChatGPT 'takes away originality', he used 'the information it gives me to form my own ideas' since 'it provided ideas to the prompt I did not think of before'.

Cluster 3: Exploratory inquirers

The largest group, Cluster 3 or exploratory inquirers, exhibited less structured and more exploratory query behaviours, characterized by shorter queries and a predominance of Explanation queries (Figure 7, left). Unlike the strategic inquirers, the exploratory inquirers relied heavily on instructor-provided guidelines to frame their interactions with ChatGPT. These assignment guidelines were often directly incorporated into the students' queries. While this approach helped students stay focused on task requirements, it also constrained the breadth of their inquiry, reducing opportunities for deeper, self-directed exploration. The predominance of Explanation queries further underscores this reliance on external scaffolding, as students typically sought detailed responses to specific assignment components rather than engaging in iterative questioning or refining their understanding. This reactive approach to interacting with ChatGPT may reflect a lack of confidence or familiarity with using AI tools independently. By adhering closely to the provided structure, these students prioritized completing the task over fostering a broader understanding or exploring creative solutions.

Bella (performance score, 70.83; 8 queries/prompts; DoK: 1; prompt relevance: 2; originality: 1; engagement: 34 out of 35; self-efficacy: 25 out of 25) relied heavily on instructor-provided guidelines to shape queries and maintain alignment with task requirements (Figure 7, right). Bella began with an Information Request. Throughout the process, she continued to use Information Request query or Explanation query to directly address key elements of the instructor guidelines, such as asking for 'the goal of the learning module' and 'plan for evaluation'. Overall, Bella's queries were tightly aligned with the instructor's framework, with little evidence of refinement or expansion beyond the prescribed elements of the project. This case highlights a key characteristic of exploratory inquirers: the tendency to use AI tools primarily as a means of reproducing externally defined structures rather than as a resource for creative problem solving or independent knowledge construction. Bella revealed in her survey and reflection that she had been using ChatGPT and 'feel more comfortable with using it', which might explain her self-efficacy level. To her, ChatGPT 'allowed me to be introduced to new ideas and use the ideas to implement into my work'. Yet, she included portions of ChatGPT outputs without sufficient modifications.

Diverse explorers and intensive explorers

Cluster 2, diverse explorers, features a more varied mix of query types. While students in Cluster 2 still engage in iterative learning, their inquiries tend to be broader or less targeted, with fewer sustained follow-up sequences like those seen in Cluster 1. Students who did not belong to the three clusters emerged as outliers (or intensive explorers), distinguished by their much higher frequency of interactions with ChatGPT, averaging 25 queries per student. Notably, performance within this group varied widely, including both very high-performing and very low-performing students. This indicates that frequent interaction with ChatGPT alone does not guarantee success; instead, the quality of engagement and how effectively students leverage the tool play critical roles.

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Qualitative strand

The open-coding process generated 105 initial codes, which were reconfigured and categorized. By examining the categories and their interconnections, we further categorized them and generated six themes following the HALIE framework. The themes, categories and sample codes can be seen in Table 6. Sample quotes can be seen in Appendix B. The majority of students identified them as nontraditional students, who rated their digital skills as average while the skills improved after the class. Some students expressed their discomfort using ChatGPT but stated the possibility of feeling differently 'if I was younger'. Despite that, as most students used ChatGPT for the first time in the classes, they became increasingly comfortable with it and showcased a growing digital capability after the experience. Theme 1 indicates these novice ChatGPT users were engaged in the ChatGPT interactions for their projects at different levels. For instance, some students used it very sparingly for initial ideas while some evaluated the outputs and followed up for more specific information. Most students still questioned their prompt engineering skills, despite a user guide provided to them upfront. Theme 2 reveals the mixed evaluation of ChatGPT outputs. After experiencing ChatGPT, some students realized and emphasized the constraints of GenAI, such as repetitive or vague outputs while others recognized the affordances, such as the visualization and breakdown of complex information. Themes 3 and 4 focus on first-person perspectives. Many students showed initial concerns about ChatGPT and were hesitant to try the tool for their work. After the experience, there was a growing acceptance of and confidence in using this technology. Most students still regarded it as a tool to jumpstart or complement their project, leading to a perceived ownership of work. While most students used the free version of ChatGPT (3.5) and strongly acknowledged the efficiency while using ChatGPT, quite a few students voiced the limitations, such as outdated and repetitive outputs which further led to a feeling of getting lost, as indicated in Theme 5. Regarding preference in

TABLE 6 Themes, categories and sample codes.

Themes	Categories	Sample codes
1. Process: novice ChatGPT users were intentionally and selectively engaged	Digital skills journey	Progress in digital capability
	Interactive engagement	Iterative prompting for better results
	Selective usage	Using ChatGPT for initial ideas/ outline
2. Output: mixed evaluation of ChatGPT outputs	ChatGPT limitations	Unclear or vague outputs
	ChatGPT affordances	Break down complex info
3. First-person perspectives: Growing acceptance of ChatGPT	Initial concerns	Ethical concerns
	Resistance	Initial hesitation/doubt
	Growing acceptance	Understanding tool's role
4. First-person perspectives: maintaining ownership of work	Ownership of work	Claiming ownership of output
	Personal accountability	Taking responsibility
	Tool versus partner	Complementary tool
5. Quality: Efficiency and limitations coexist	Time efficiency	Time-saving benefits
	Output accuracy	Outdated information
	Technical limitations	Get lost in long output
6. Preference: Enjoyment and continuous usage intention	Enjoyment	Positive experience
		Negative experience
	Willingness to reuse	Plans for future use

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Theme 6, several students spoke very negatively but most people expressed how they were 'fascinated' by the performance of ChatGPT and have a strong willingness to continue using it in future classes and jobs.

DISCUSSION

In this study, we tried to provide a comprehensive picture of nontraditional students' interactions with ChatGPT to facilitate their learning through quantitative and qualitative approaches. We analysed four metrics in the quantitative strand, including prompt number, DoK, prompt relevance and originality. The average prompt number was seven, reflecting students' limited time on task as they engaged with instructional design tasks, such as developing training proposals or analysing trends and cases. The qualitative findings showed their growing acceptance of ChatGPT but also revealed their initial concerns and resistance, which might explain the relatively low prompt numbers. The DoK level hovered around Level 2, indicating a focus on lower-order thinking skills like recall and reproduction, with minimal application of concepts. Nontraditional students in this class were still progressing in their digital capacity being the first-time user of ChatGPT as they stated in the interviews. Even though they interactively engaged in the activity, the engagement was selective, with most of them using ChatGPT for initial ideation, resulting in low DoK levels. Prompt relevance revealed a pattern of isolated and narrowly scoped queries, showing limited progression in complexity and specificity. Originality, on the other hand, demonstrated moderate levels, with some students significantly modifying ChatGPT's output by incorporating their ideas and creativity. It was also reflected in one of the themes in the qualitative analysis, that learners maintained ownership of work as they used it as a supplementary tool and took accountability of their work. This may, in part, reflect the high creative skills often observed in and associated with nontraditional students, such as neurodivergent learners (Hayashibara et al., 2023; Pasarín-Lavín et al., 2024). While students exhibited originality, the other metrics suggest they are still developing skills in effectively leveraging ChatGPT as a learning tool. Positive correlations between prompt numbers and both DoK and relevance suggest that training students to craft more prompts may deepen their engagement with content. However, originality's negative correlation with both DoK and relevance may suggest potential over-reliance on ChatGPT (Fuchs, 2023; Sok & Heng, 2023; Stojanov et al., 2024), where dense interactions with the tool may not equate to genuine, independent thought. Our findings on the negative correlation between originality and both DoK and prompt relevance align with recent empirical evidence on AI over-reliance patterns (Zhai et al., 2024). While students in our study demonstrated high self-efficacy and engagement with AI tools, which might partially be attributed to the video tutorials and guidelines, this confidence may actually enable problematic dependency. Malik et al. (2023) found in their survey that 75% of studied learners reported reduced critical thinking despite feeling comfortable using AI tools. The interaction patterns we observed, particularly among exploratory inquirers who relied heavily on isolated, narrow queries, mirror the concerning behaviours documented by Duhaylungsod and Chavez (2023), where over-reliance led to complacency and undue dependence on AI dialogue systems.

The contrast between our strategic inquirers, who maintained higher originality through purposeful questioning, and other groups who showed lower originality scores despite frequent AI use, is consistent with Kim et al.'s (2023) finding that simplified AI interactions can undermine learners' independent analytical capabilities. Our results showing high engagement but reduced originality particularly resonate with Santiago Jr. et al.'s (2023) faculty observations about AI tools potentially impeding critical thinking development despite increasing surface-level task completion. As Grassini (2023) demonstrated through empirical

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

analysis, the convenience of AI assistance can mask a decline in students' analytical capabilities. This is a pattern that helps explain why we found higher self-efficacy correlating with lower originality scores.

The findings from the qualitative data may shed light on students' interaction behaviours. Most students had never heard of or used ChatGPT prior to the class. Besides low comfort with and confidence in using such a new tool, some of them had strong privacy or ethical concerns or resistance that prevented them from fully engaging with it, which echoes prior literature (Adel et al., 2024; Guleria et al., 2023; Luo et al., 2024). Despite being impressed by the performance of ChatGPT, students admitted to using ChatGPT sparingly as a starting point. Notably, they were less concerned after the class and showed more willingness to be more engaged. The text mining approach revealed three clusters and one outlier cluster based on their query patterns. Cluster 1 students (13%) were identified as strategic inquirers with distinctly more follow-ups from information requests and explanations, compared with Cluster 2 diverse explorers who asked a mix of query types, and Cluster 3 exploratory inquirers who mainly used shorter explanation queries.

The quantitative analyses revealed the significance of prompt number and engagement level in predicting performance scores and several pairs of significant correlations among the ChatGPT interactions. Prompt numbers, as a behavioural indicator of time on task similarly to the number of discussion posts, naturally aligned with higher performance, echoing prior research linking engagement to learning outcomes (Zheng & Warschauer, 2015). Self-efficacy was positively and significantly correlated with engagement, yet it was not a significant predictor for performance, possibly due to calibration issues where students' perceived confidence did not align with their actual capabilities (Bol & Hacker, 2012). Qualitative findings suggest that as students became more comfortable using ChatGPT, they may have tended to over-rely on the tool, which inadvertently hindered originality in their assignments. This reliance could explain the negative relationship between self-efficacy and originality, as students may increasingly adopt ChatGPT's output without substantial personal contribution. Students' DoK and prompt relevance levels are also significantly correlated with their performance, indicating that a higher level of thinking and reasoning in interacting with ChatGPT and more relevant prompts tend to be associated with a higher level of performance. By examining the relationships among the ChatGPT interactions, we found that prompt number, DoK and prompt relevance are significantly related to each other, while originality is significantly negatively related to DoK and prompt relevance. These findings underscore the nuanced and intricate relationships between engagement, self-efficacy, interactions and performance in a ChatGPT-facilitated learning environment, warranting further exploration (Liang et al., 2023; Shahzad et al., 2024).

The findings from Cluster 1, for example, highlighted the potential for AI tools to support purposeful, inquiry-driven learning when students adopted structured interaction strategies. Educational interventions designed to scaffold such strategies—for example, teaching students how to formulate effective follow-up questions or encouraging iterative inquiry—could help other learners replicate the successful behaviours observed in this cluster. To support students like Bella from Cluster 3, educational interventions could encourage more active and reflective engagement with AI tools. For example, students could be prompted to go beyond reproducing the guidelines by generating additional follow-up questions, exploring the reasoning behind their choices or considering alternative approaches to the task. Practically speaking, these results suggest that educators need to provide targeted guidance on integrating ChatGPT into learning and design environments. Despite a user guide and video demo on using ChatGPT, which were perceived as very helpful resources, students' interactions with the tool largely remained at lower to medium cognitive levels as they lacked the skills to engage in ChatGPT at high cognitive levels. Therefore, we suggest that prompt engineering should be explicitly taught as a critical skill to empower learners to engage in

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

higher-order thinking and problem-solving (Gregory, 2024). Educators should also emphasize the importance of balancing ChatGPT's affordances with critical, independent thinking to avoid over-reliance on GenAI-generated outputs (Luo et al., 2024). Academic institutions and organizations should consider investing in AI literacy training that raises awareness about the limitations and ethical considerations of GenAI tools (Luo et al., 2024). To respect the diversity in students' learning journeys, instructors should consider offering personalized feedback and guidance that aligns with each student's approach and needs.

IMPLICATIONS FOR RESEARCH AND PRACTICE

This study is among the first to examine and evaluate learners' GenAI interactions and the interplay between interaction, engagement, self-efficacy and performance in a ChatGPT-facilitated learning environment using a mixed-methods approach. We adapted the HALIE framework to guide our study and adopted the DoK levels to understand students' cognitive engagement in the complex problem-solving process facilitated by ChatGPT. By investigating the interactions through multiple metrics, instructors and researchers can gain insights into the depth of cognitive engagement and the sophistication of AI tool use. Future research should adapt and improve these metrics in other tasks or contexts to identify areas where learners may need additional support in leveraging AI tools more effectively for higher-order thinking tasks. In this study, we did not find the significance of students' self-efficacy in predicting their performance, which might be counterintuitive. The survey was deployed at the end of the semester. We recommend future studies to conduct a pre-survey as well to have a more accurate measurement of learners' self-efficacy at the time of using the AI tools. Additionally, future research can consider incorporating originality as a criterion in measuring performance, instead of treating it as a separate variable, to better capture a more nuanced understanding of learning outcomes as it can assess learners' genuine learning and creativity while still acknowledging the role of AI as a supportive tool.

Examining nontraditional students' technology usage and efficacy remains underexplored (Sutherland et al., 2024), especially the integration of AI. Nontraditional students, as a growing population in higher education over the past decade, require even more support when it comes to technology integration due to the traditional digital divide (Banerjee, 2020; Sutherland et al., 2024). In the era of AI, to prepare the future workforce with the needed digital competencies, more attention should be placed to support nontraditional students. Considering their characteristics, we recommend instructors include more targeted technology training and practice when applicable, along with resources supporting their self-paced learning. Students in this class recognized the usefulness of a ChatGPT user guide and a video demo created by the research team. Instructors can create microlearning modules (eg, short videos and text-based job aids) prior to the integration of new tools in coursework to facilitate a more positive learning experience.

LIMITATIONS

We acknowledge that the quantitative sample size was not large enough, restricting the use of more robust analytical techniques. Considering the unique context of the present study, the generalizability of the findings might be limited when extended to other types of student populations. Our participants primarily consisted of nontraditional students in the United States who often might face unique challenges compared with those in other countries or areas. Those characteristics might not match with traditional student populations. However, we followed a rigorous research design and provided transparency in our methodology for

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

future adaptation and application in other contexts. For example, the metrics to evaluate ChatGPT interactions can be replicated or adapted in studies involving traditional students or other learner demographics. Additionally, synthesizing data from diverse sources posed challenges, and unique nuances across the undergraduate and graduate courses were not fully captured. The study also did not comprehensively account for the varied characteristics of nontraditional learners (ie, age and employment status). Future research should address these limitations by using larger sample sizes and more disaggregated data to explore fine-grained differences based on nontraditional status. Additionally, future research could benefit from in-depth qualitative approaches, such as phenomenology or narrative inquiry, to provide valuable contextual insights into the unique lived experiences and perspectives of individual participants using ChatGPT for their learning and how such use may impact learning outcomes around engagement, performance and self-efficacy.

CONCLUSION

In this mixed-methods research, we explored nontraditional students' ChatGPT interactions to facilitate their instructional design, model creation, case development and trends analysis projects. By adapting the HALIE framework, we conducted quantitative tests, qualitative thematic analysis and text mining techniques to examine students' ChatGPT interaction and relationships between the variables. The results revealed different query patterns, a relatively low average depth of knowledge and prompt relevance, yet significant associations with performance. Prompt number and engagement were key significant predictors of performance. All ChatGPT interaction characteristics examined in this study were significantly correlated with each other. The findings underscore the importance of analysing learners' GenAI interactions to inform course designs that foster learners' engagement and critical thinking.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest regarding the research.

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

DATA AVAILABILITY STATEMENT

The datasets of the current study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

The Old Dominion University Education Human Subjects Review Committee (2103003-2) has approved this study. Students were assigned pseudonyms in the manuscript.

ORCID

Mohan Yang https://orcid.org/0000-0003-0856-0814
Shiyan Jiang https://orcid.org/0000-0003-4781-846X

REFERENCES

Adel, A., Ahsan, A., & Davison, C. (2024). ChatGPT promises and challenges in education: Computational and ethical perspectives. *Education Sciences*, *14*(8), 814. https://doi.org/10.3390/educsci14080814

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Alt, D., & Raichel, N. (2020). Enhancing perceived digital literacy skills and creative self-concept through gamified learning environments: Insights from a longitudinal study. *International Journal of Educational Research*, *101*, 101561. https://doi.org/10.1016/j.ijer.2020.101561

Avey, J. B., Avolio, B. J., Crossley, C. D., & Luthans, F. (2009). Psychological ownership: Theoretical extensions, measurement and relation to work outcomes. *Journal of Organizational Behavior*, *30*(2), 173–191. https://doi.org/10.1002/job.583

Barber, J. (2018). Depth of knowledge and conceptual understanding. *Science Scope* , *41*(9), 76–81.

Banerjee, M. (2020). An exploratory study of online equity: Differential levels of technological access and technological efficacy among underserved and underrepresented student populations in higher education. *Interdisciplinary Journal of e-Skills and Lifelong Learning*, *16*, 93–121. https://doi.org/10.28945/4664

Bauer, L., Burtis, E., Howard, O., & Wang, S. Y. (2023). *Which nontraditional students are also in the labor force?* The Hamilton Project. https://www.hamiltonproject.org/publication/post/which-nontraditional-students-are-also-in-the-labor-force/

Bean, J. P., & Metzner, B. S. (1985). A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research*, *55*(4), 485–540. https://doi.org/10.3102/00346543055004485

Bol, L., & Hacker, D. J. (2012). Calibration research: Where do we go from here? *Frontiers in Psychology*, *3*, 229. https://doi.org/10.3389/fpsyg.2012.00229

Bolick, A. D., & da Silva, R. L. (2024). Exploring artificial intelligence tools and their potential impact to instructional design workflows and organizational systems. *TechTrends*, *68*, 91–100. https://doi.org/10.1007/s11528-023-00894-2

Cavazos, J. T., Hauck, K. A., Baskin, H. M., & Bain, C. M. (2024). ChatGPT goes to college: Exploring student perspectives on artificial intelligence in the classroom. *Teaching of Psychology*. https://doi.org/10.1177/00986283241268829

Champa, A. I., Rabbi, M. F., Nachuma, C., & Zibran, M. F. (2024). ChatGPT in action: Analyzing its use in software development. In *Proceedings of the 21st International Conference on Mining Software Repositories* (pp. 182–186).

Chang, D. H., Lin, M. P. C., Hajian, S., & Wang, Q. Q. (2023). Educational design principles of using AI chatbot that supports self-regulated learning in education: Goal setting, feedback, and personalization. *Sustainability*, *15*(17), 12921. https://doi.org/10.3390/su151712921

Choy, S. (2002). *Nontraditional undergraduates: Findings from "the condition of education, 2002"*. National Center for Education Statistics.

Clarke, V., & Braun, V. (2017). Thematic analysis. *The Journal of Positive Psychology*, *12*(3), 297–298.

Cleveland-Innes, M. (1994). Adult student drop-out at post-secondary institutions. *The Review of Higher Education*, *17*(4), 423–445. https://doi.org/10.1353/rhe.1994.0011

Creswell, J. W., & Clark, V. L. P. (2017). *Designing and conducting mixed methods research*. Sage Publications.

Dell'Acqua, F., McFowland III, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., & Lakhani, K. R. (2023). *Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality*. Harvard Business School Technology & Operations Management. Unit Working Paper (24-013).

Dolch, C., & Zawacki-Richter, O. (2018). Are students getting used to learning technology? Changing media usage patterns of traditional and non-traditional students in higher education. *Research in Learning Technology*, *26*. https://doi.org/10.25304/rlt.v26.2038

Duhaylungsod, A. V., & Chavez, J. V. (2023). ChatGPT and other AI users: Innovative and creative utilitarian value and mindset shift. *Journal of Namibian studies: History Politics Culture*, *33*, 4367–4378. https://doi.org/10.59670/jns.v33i.2791

Escalante, J., Pack, A., & Barrett, A. (2023). AI-generated feedback on writing: Insights into efficacy and ENL student preference. *International Journal of Educational Technology in Higher Education*, *20*, 57. https://doi.org/10.1186/s41239-023-00425-2

Francis, E. (2021). *Deconstructing depth of knowledge*. Solution Tree.

Fairlie, R. W., & London, R. A. (2012). The effects of home computers on educational outcomes: Evidence from a field experiment with community college students. *The Economic Journal*, *122*(561), 727–753. https://doi.org/10.1111/j.1468-0297.2011.02484.x

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Fredricks, J. A., & McColskey, W. (2012). The measurement of student engagement: A comparative analysis of various methods and student self-report instruments. In *Handbook of research on student engagement* (pp. 763–782). Springer US.

Fuchs, K. (2023). Exploring the opportunities and challenges of NLP models in higher education: Is chat GPT a blessing or a curse? *Frontiers in Education*, *8*, 1166682. https://doi.org/10.3389/feduc.2023.1166682

Harris, M. A., & Patten, K. P. (2015). Using Bloom's and Webb's taxonomies to integrate emerging cybersecurity topics into a computing curriculum. *Journal of Information Systems Education*, *26*(3), 219–234.

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Hess, K. K., Jones, B. S., Carlock, D., & Walkup, J. R. (2009). Cognitive rigor: Blending the strengths of Bloom's Taxonomy and Webb's Depth of Knowledge to enhance classroom-level processes. *Educational Psychology Review*, *21*(4), 383–401.

Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and chatGPT in educational settings. *Education Sciences*, *13*(7), 692. https://doi.org/10.3390/educsci13070692

Gregory, S. F. (2024). Empowering teaching with prompt engineering: How to integrate curriculum, standards, and assessment for a new age. In *Transforming education with generative AI: Prompt engineering and synthetic content creation* (pp. 239–260). IGI Global.

Guleria, A., Krishan, K., Sharma, V., & Kanchan, T. (2023). ChatGPT: Ethical concerns and challenges in academics and research. *The Journal of Infection in Developing Countries*, *17*(9), 1292–1299. https://doi.org/10.3855/jidc.18738

Halverson, L. R., & Graham, C. R. (2019). Learner engagement in blended learning environments: A conceptual framework. *Online Learning*, *23*(2), 145–178. https://doi.org/10.24059/olj.v23i2.1481

Hayashibara, E., Savickaite, S., & Simmons, D. (2023). Creativity and neurodiversity: Towards an inclusive creativity measure for autism and ADHD. OSF preprint. https://doi.org/10.31219/osf.io/4vqh5

Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education*, *90*, 36–53. https://doi.org/10.1016/j.compedu.2015.09.005

Holmegaard, H. T., Madsen, L. M., & Ulriksen, L. (2017). Why should European higher education care about the retention of non-traditional students? *European Educational Research Journal*, *16*(1), 3–11. https://doi.org/10.1177/1474904116683688

Horn, L., Nevill, S., & Griffith, J. (2006). *Profile of undergraduates in US postsecondary education institutions, 2003-04: With a special analysis of community college students*. Statistical Analysis Report, NCES 2006-184. National Center for Education Statistics.

Jesnek, L. M. (2012). Empowering the non-traditional college student and bridging the "digital divide". *Contemporary Issues in Education Research*, *5*(1), 1–8.

Jiang, S., Tatar, C., & Xie, C. (2021). Augmented reality in science laboratories: Investigating high school students' navigation patterns and their effects on learning performance. *Educational Technology Research and Development*, *60*(3). https://doi.org/10.1177/07356331211038764

Jones, D. J., & Watson, B. C. (1990). *High-risk students and higher education: Future trends*. ASHE-ERIC Higher Education Report No. 3. The George Washington University.

Kim, Y., Lee, M., Kim, D., & Lee, S.-J. (2023). Towards explainable AI writing assistants for non-native English speakers. *arXiv preprint arXiv:2304.02625*.

Kumar, H., Musabirov, I., Reza, M., Shi, J., Wang, X., Williams, J. J., Kuzminykh, A., & Liut, M. (2024). Impact of guidance and interaction strategies for LLM use on learner performance and perception. *arXiv preprint arXiv:2310.13712*.

Kuo, Y. (2018). An exploratory study of minority students' technology usage and perceptions of technology: Nontraditional adult students in technology-based environments. *Journal of Research on Technology in Education*, *50*(4), 350–364. https://doi.org/10.1080/15391523.2018.1522984

Lee, M., Srivastava, M., Hardy, A., Thickstun, J., Durmus, E., Paranjape, A., Gerard-Ursin, I., Li, X. L., Ladhak, F., Rong, F., Bose, S., Kennedy, B., Xiong, C., Strobelt, H., Luu, L., Whittaker, M., Wu, J., Srinivasan, A., Chilton, L., & Liang, P. (2023). Evaluating human-language model interaction. *arXiv preprint arXiv:2212.09746*.

Li, B., Bonk, C. J., Wang, C., & Kou, X. (2024). Reconceptualizing self-directed learning in the era of generative AI: An exploratory analysis of language learning. *IEEE Transactions on Learning Technologies*, *17*(4), 1515–1529. https://doi.org/10.1109/TLT.2024.3386098

Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: Serial mediating roles of self-efficacy and cognitive engagement. *Frontiers in Psychology*, *14*, 1285392. https://doi.org/10.3389/fpsyg.2023.1285392

Lo, C. K., Hew, K. F., & Jong, M. S. Y. (2024). The influence of ChatGPT on student engagement: A systematic review and future research agenda. *Computers & Education*, *219*, 105100. https://doi.org/10.1016/j.compedu.2024.105100

Lombard, E. (2022). Do you want this double or single spaced? Transactional versus transformational questions. *Journal of Education and Learning*, *11*(5), 124. https://doi.org/10.5539/jel.v11n5p124

Luo, T., Muljana, P. S., Ren, X., & Young, D. (2024). Exploring instructional designers' utilization and perspectives on generative AI tools: A mixed methods study. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-024-10437-y

Malik, A. R., Pratiwi, Y., Andajani, K., Numertayasa, I. W., Suharti, S., & Darwis, A. (2023). Exploring artificial intelligence in academic essay: Higher education student's perspective. *International Journal of Educational Research Open*, *5*, 100296. https://doi.org/10.1016/j.ijedro.2023.100296

Markle, G. (2015). Factors influencing persistence among nontraditional university students. *Adult Education Quarterly*, *65*(3), 267–285. https://doi.org/10.1177/0741713615583085

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Morgan, J. J., Brown, N. B., Hsiao, Y.-J., Howerter, C., Juniel, P., Sedano, L., & Castillo, W. L. (2014). Unwrapping academic standards to increase the achievement of students with disabilities. *Intervention in School and Clinic*, *49*(3), 131–141. https://doi.org/10.1177/1053451213496156

National Center for Education Statistics. (1999). *National Postsecondary Student Aid Study (NPSAs)*. U.S. Department of Education. https://nces.ed.gov/statprog/handbook/npsas.asp

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

Pasarín-Lavín, T., García, T., Abín, A., & Rodríguez, C. (2024). Neurodivergent students. A continuum of skills with an emphasis on creativity and executive functions. *Applied Neuropsychology: Child*, 1–13. https://doi.org/10.1080/21622965.2024.2406914

Reschly, A. L., & Christenson, S. L. (2012). Jingle, jangle, and conceptual haziness: Evolution and future directions of the engagement construct. In *Handbook of research on student engagement* (pp. 3–19). Springer US.

Santiago Jr, C. S., Embang, S. I., Conlu, M. T. N., Acanto, R. B., Lausa, S. M., Ambojia, K. W. P., Laput, E. Y., Aperocho, M. D. B., Malabag, B. A., & Balilo, B. B., Jr. (2023). Utilization of writing assistance tools in research in selected higher learning institutions in the Philippines: A text mining analysis. *International Journal of Learning, Teaching and Educational Research*, *22*(11), 259–284. https://doi.org/10.26803/ijlter.22.11.14

Sapir, A. (2022). What student support practitioners know about non-traditional students: A practice-based approach. *Higher Education Research and Development*, *41*(6), 2064–2078.

Shahzad, M. F., Xu, S., & Zahid, H. (2024). Exploring the impact of generative AI-based technologies on learning performance through self-efficacy, fairness & ethics, creativity, and trust in higher education. *Education and Information Technologies*, *30*(3), 1–26. https://doi.org/10.1007/s10639-024-12949-9

Shepherd, M. M., & Sheu, T. S. (2014). The effects of informal faculty-student interaction and use of information technology on non-traditional students' persistence intentions and educational outcomes. *Journal of Higher Education Theory & Practice*, *14*(2), 46–60.

Skinner, E. A., Kindermann, T. A., & Furrer, C. J. (2009). A motivational perspective on engagement and disaffection: Conceptualization and assessment of children's behavioral and emotional participation in academic activities in the classroom. *Educational and Psychological Measurement*, *69*(3), 493–525. https://doi.org/10.1177/0013164408323233

Sok, S., & Heng, K. (2023). ChatGPT for education and research: A review of benefits and risks. *Cambodian Journal of Educational Research*, *3*(1), 110–121. https://doi.org/10.62037/cjer.2023.03.01.06

Stojanov, A., Liu, Q., & Koh, J. H. L. (2024). University students' self-reported reliance on ChatGPT for learning: A latent profile analysis. *Computers and Education: Artificial Intelligence*, *6*, 100243. https://doi.org/10.1016/j.caeai.2024.100243

Sulecio de Alvarez, M. S., & Dickson-Deane, C. (2018). Avoiding educational technology pitfalls for inclusion and equity. *TechTrends*, *62*(4), 345–353. https://doi.org/10.1007/s11528-018-0270-0

Sutherland, K., Brock, G., de Villiers Scheepers, M. J., Millear, P. M., Norman, S., Strohfeldt, T., Downer, T., Masters, N., & Black, A. L. (2024). Non-traditional students' preferences for learning technologies and impacts on academic self-efficacy. *Journal of Computing in Higher Education*, *36*(2), 298–319. https://doi.org/10.1007/s12528-023-09354-5

Traynor, A., Li, T., & Zhou, S. (2020). Gauging uncertainty in test-to-curriculum alignment indices. *Applied Measurement in Education*, *33*(2), 141–158. https://doi.org/10.1080/08957347.2020.1732387

Uddin, S. J., Albert, A., Ovid, A., & Alsharef, A. (2023). Leveraging ChatGPT to aid construction hazard recognition and support safety education and training. *Sustainability*, *15*(9), 7121. https://doi.org/10.3390/su15097121

Webb, N. L. (2002). Depth-of-knowledge levels for four content areas. *Language Arts*, *28*, 1–9.

White, J., Fu, Q., Hays, S., Sandborn, M., Olea, C., Gilbert, H., Elnashar, A., Spencer-Smith, J., & Schmidt, D. C. (2023). A prompt pattern catalog to enhance prompt engineering with ChatGPT. *arXiv preprint arXiv:2302.11382*.

Wittwer, J., & Renkl, A. (2010). How effective are instructional explanations in example-based learning? A meta-analytic review. *Educational Psychology Review*, *22*(4), 393–409. https://doi.org/10.1007/s10648-010-9136-5

Wyse, A. E., & Viger, S. G. (2011). How item writers understand depth of knowledge. *Educational Assessment*, *16*(4), 185–206. https://doi.org/10.1080/10627197.2011.634286

Yan, L., Martinez-Maldonado, R., & Gašević, D. (2024). Generative artificial intelligence in learning analytics: Contextualising opportunities and challenges through the learning analytics cycle. In *Proceedings of the 14th International Conference on Learning Analytics & Knowledge* (pp. 101–111). https://doi.org/10.1145/3636555.3636856

Zamfirescu-Pereira, J. D., Wong, R. Y., Hartmann, B., & Yang, Q. (2023). Why Johnny can't prompt: How non-AI experts try (and fail) to design LLM prompts. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1–21). https://doi.org/10.1145/3544548.3581388

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments*, *11*(1), 28. https://doi.org/10.1186/s40561-024-00316-7

Zhang, P., & Tur, G. (2023). A systematic review of ChatGPT use in K-12 education. *European Journal of Education*, *59*(2), e12599. https://doi.org/10.1111/ejed.12599

Zheng, B., & Warschauer, M. (2015). Participation, interaction, and academic achievement in an online discussion environment. *Computers & Education*, *84*, 78–89. https://doi.org/10.1016/j.compedu.2015.01.008

How to cite this article: Yang, M., Jiang, S., Li, B., Herman, K., Luo, T., Moots, S. C., & Lovett, N. (2025). Analysing nontraditional students' ChatGPT interaction, engagement, self-efficacy and performance: A mixed-methods approach. *British Journal of Educational Technology*, *56*, 1973–2000. https://doi.org/10.1111/bjet.13588

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

APPENDIX A

ChatGPT INTERACTION METRICS

Depth of Knowledge (DoK)

Recall and recognition of factual info (1)	Skills and concepts processing (2)	Strategic thinking and reasoning (3)	Extended thinking (4)
1. Prompts that require basic recall of facts, definitions or simple procedures 2. Low cognitive demand, straightforward and typically single-step questions 3. Little to no follow-up or deeper engagement with ChatGPT responses	1. Prompts that require comprehension and processing of information or ChatGPT outcomes 2. Involve more than one step but still relatively straightforward 3. Some follow-up questions show an attempt to build on previous responses	1. Prompts that require reasoning, planning and using evidence 2. More complex and abstract, often involving multiple steps and deeper analysis 3. Follow-up questions build on previous interactions to explore topics more deeply	1. Prompts that require complex reasoning, planning, developing and evaluating 2. Involve multiple steps and sustained effort over a longer period 3. Follow-up questions show a sophisticated development and refinement of ideas

Prompt relevance and evolution

Low relevance and evolution (1)	Limited relevance and limited evolution (2)	Moderate relevance and clear evolution (3)	High relevance and advanced evolution (4)
1. Prompts are largely unrelated to each other 2. Little to no narrowing of scope; prompts are broad and disconnected 3. No clear progression or development in the line of questioning	1. Prompts show some relevance to each other but lack depth and focus 2. Limited narrowing of scope; some prompts build on previous ones but not consistently 3. Minimal progression in the complexity and specificity of questions	1. Prompts are mostly relevant and build on each other with a clear line of questioning 2. Noticeable narrowing of scope; prompts become more focused and detailed 3. Clear progression in the complexity and specificity of questions	1. Prompts are highly relevant and show a strong development of ideas 2. Clear narrowing of scope with highly focused and interrelated prompts 3. Advanced progression in the complexity, specificity and depth of questions

Originality

Low originality (1)	Limited originality (2)	Moderate originality (3)	High originality (4)
• The topic idea was purely from ChatGPT • Direct copying and pasting from ChatGPT without any modification • Minimal to no personal input or original content • Reliance entirely on ChatGPT's responses	• The selection of the topic idea was generated based on the interaction with ChatGPT • Some modification of ChatGPT's output but still heavily reliant on AI-generated content • Limited personal input and minimal original content • Basic attempts to paraphrase or slightly modify ChatGPT's responses	• Idea was from student but refined based on the interaction with ChatGPT • Significant modification of ChatGPT's output with substantial personal input • Integration of personal ideas, analysis and creativity • Effective use of ChatGPT as a tool to support and enhance original work	• Students had a clear training idea from the beginning • Extensive and sophisticated use of ChatGPT to refine and enhance original content • High degree of personal input, creativity and critical thinking • Consistent and purposeful prompting and training of ChatGPT to obtain desired outputs

APPENDIX B

SAMPLE QUOTES FOR THE THEMES AND CATEGORIES

Themes	Categories	Sample codes	Sample quotes
1. Process: novice ChatGPT users were intentionally and selectively engaged	Digital skills journey	Progress in digital capability	*Since I was initially unfamiliar with ChatGPT I wasn't confident that I would know how to complete the proposal assignment. By reviewing the resources, videos and instructions I was able to overcome any technological barriers*
	Interactive engagement	Iterative prompting for better results	*For example, I said give me a proposal for overlanding. It gave me a generalization and a format, but I was like, Okay, well, this is not really college level. So I said give me a college type proposal for overlanding. And then it re-scribed it on how I wanted it to be with college literacy*
	Selective usage	Using ChatGPT for initial ideas/outline	*I'm using it more because we're required to interact with it…if we were given the opportunity to use it or not use it, I would probably be more of an 80 I probably wouldn't use it and 20 I probably would just to get that extra feedback. Like to get that extra little… like something that I might have missed*
2. Output: Mixed evaluation of ChatGPT outputs	ChatGPT limitations	Unclear or vague outputs	*I say the biggest challenge I would have is the, I will say, ambiguity, but the lack of long established precedents on like, citation and accreditation or, you know, using it without encountering problems with plagiarism, you know what I mean?*
	ChatGPT affordances	Jump start the project	*…used my thoughts to create certain things and it allowed me to be introduced to new ideas and use the ideas to implement into my work. ChatGPT acted as a ladder for me to climb to elevate my projects*

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Themes	Categories	Sample codes	Sample quotes
3. First-person perspectives: Growing acceptance of ChatGPT	Resistance	Ethical concerns	*I've had others, like younger students say, well, hey, why don't you just, you know, use the ChatGPT for this, you know, it's so much quicker, so much easier. And I'm like, that's fine, but as a person going back to, you know, saying, morally, our ethics, stuff like that. What am I teaching myself? I'm teaching myself the quick, easy way to get an answer. But it does me no good, especially if I'm in the workforce, and say that I'm in a meeting with the board of directors for something and it's like, hey, hold on a minute. I need to get my ChatGPT up so I can give you this answer. So what have I taught myself morally? Nothing really*
	Cognitively challenged	Think outside the box	*Its ability to offer diverse perspectives and suggestions that I might not have considered otherwise. It helped me think outside the box and explore different angles for my eLearning proposal*
	Growing acceptance	Understanding tool's role	*I guess we all, it sounds like everyone here figured out that it works and can help. Maybe throughout the course of the class, some of us already knew. But others may have grown to that realization that it's not a boogeyman. It's not going to do anything crazy. It'll do what you ask it to do*
4. First-person perspectives: Maintaining ownership of work	Ownership of work	Ownership of process	*I felt as if ownership was not 100% mine, but I felt as if it was an easier way to research a topic as you would with anything and get your results all in one place. I did feel I owned more of the learning process as I provided the prompts and tailored them to my specific needs*
	Personal accountability	Taking responsibility	*I feel accountable with anything that I use with chat GPT because I feel like even though it's always right, I always like to fact checked it fact check it. So if it were to like, give me an idea or a topic, I'm like, Okay, let me go find some references that I can use to support this idea and not just use it on my own. Being accountable means that I can stand by what I say no matter if I get the idea or topic from chat GPT or on my own, and being able to like defend it*
	Tool versus partner	Complementary tool	*I see it as a tool. But I know that we have to go further than that. I mean, just because chat and AI are opening all kinds of doors for all kinds of other things. I just wanted to add that what I, what I feel is that it complements my work, that it helps me get it done faster. So it's more efficient for me. I don't get stuck and I don't have to sit there and think for hours on something when I can ask the question if that makes sense*

(Continues)

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Themes	Categories	Sample codes	Sample quotes
5. Quality: Efficiency and limitations coexist	Time efficiency	Time-saving benefits	*I feel as if I'm learning more at a faster rate when using it because it's giving me exactly what I'm asking for, which reduces research time dramatically*
	Output accuracy	Outdated information	*I think it tells you in the User Agreement that it only goes up to 2022 publication, or either two, I'm pretty sure it's 2022. So, it's not very up to date*
	Technical limitations	Get lost in long output	*You've already kind of got in mind what you're going to do, and as I started chatting with, you know, the AI stuff…I find myself starting to dig in deeper, okay, I want more detail. I don't want the same thing…So I find myself two hours into this chatting with this thing and it's still not gotten me anywhere, where what I'm looking for*
6. Preference: Enjoyment and continuous usage intention	Enjoyment	Positive experience	*My experience with ChatGPT was incredibly positive. AI was able to provide me with valuable insights and suggestions to help me refine my proposal development process. I found the responses to be relevant, well-researched and overall, very helpful in guiding me towards a more polished product*
		Negative experience	*It seems like a true waste of the opportunity of knowledge. I do not like using ChatGPT, it takes all creativity out of the picture and also does not allow us to learn things organically*
	Willingness to reuse	Plans for future use	*Now I see that it can be used for much more than completely doing your assignments. I will be using it more often*

14678535, 2025, 5, Downloaded from https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.13588 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License