How Students (Really) Use ChatGPT: Uncovering Experiences Among Undergraduate Students

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This study investigates how undergraduate students engage with ChatGPT in self-directed learning contexts. Analyzing naturalistic interaction logs, we identify five dominant use categories of ChatGPT-information seeking, content generation, language refinement, meta-cognitive engagement, and conversational repair. Behavioral modeling reveals that structured, goal-driven tasks like coding, multiple-choice solving, and job application writing are strong predictors of continued use. Drawing on Self-Directed Learning (SDL) and the Uses and Gratifications Theory (UGT), we show how students actively manage ChatGPT's affordances and limitations through prompt adaptation, follow-ups, and emotional regulation. Rather than disengaging after breakdowns, students often persist through clarification and repair, treating the assistant as both tool and learning partner. We also offer design and policy recommendations to support transparent, responsive, and pedagogically grounded integration of generative AI in higher education.

CCS Concepts: \bullet Human-centered computing \rightarrow Human computer interaction (HCI).

Additional Key Words and Phrases: ChatGPT, self-directed learning, generative AI, student engagement, educational technology, human-AI interaction, prompt engineering, uses and gratifications, learning analytics, conversational AI, higher education

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1 Introduction

The rapid proliferation of large language models and AI-driven chatbots, exemplified by ChatGPT, is reshaping how learners search for information, plan assignments, and solicit feedback. Yet despite the tool's visibility, we still lack a clear picture of the day-to-day ways students weave it into their holistic academic routines that that encompass not only formal coursework, but also the personal, logistical, and informal practices through which students manage, experience, and make meaning of learning in everyday life. Most of what is known comes from self-reports, single-course case studies, or public prompt repositories, leaving fundamental questions unanswered about what students actually ask ChatGPT to do—and how that use evolves across a semester [18, 115, 121].

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This gap matters because institutions are already writing policies and building infrastructure around generative AI [65]. OpenAI's release of ChatGPT Edu in May 2024, created in partnership with several United States universities, has accelerated both investment and anxiety over responsible deployment [32, 100]. Administrators need evidence to decide whether the tool augments learning or erodes it, instructors need guidance on scaffolding its use, and students need to understand the trade-offs they face in terms of trust, privacy, and academic integrity. Without a fine-grained account of real usage, well-intentioned policies risk being either toothless or overly restrictive.

Studying this phenomenon present several methodological and conceptual challenges. ChatGPT interactions are self-directed, cross disciplinary boundaries, and change as the model and interface are updated, making them difficult to capture through traditional research designs. Existing studies have approached this topic through self-report surveys [18, 112, 121], qualitative analysis of interviews [2, 119], publicly available datasets (e.g., Wildchat; [138] or ShareGPT; [39]), partial user logs [115]. While these efforts have provided useful insights, they often rely on narrow slices of data and are limited in their ability to track the evolving, iterative nature of real-world use. For example, laboratory prompts or single-session surveys often miss the iterative strategies students employ when a response is confusing, hallucinated, or misaligned with an assignment's rubric. Crafting an effective prompt itself is an important skill, and users frequently iterate through multiple revisions before achieving a satisfactory answer [26, 134]. Moreover, the same interaction may fulfill academic, emotional, or logistical needs at the same time, complicating attempts to assign clean functional labels.

Compounding these challenges is the field's fragmented disciplinary focus. Much of the existing literature centers on specific domains like computer science and engineering (e.g., [4, 60, 94, 125, 132], English as Foreign Language (EFL) writing courses [73], isolating specific skills like learning to code [50, 54, 56, 59, 139] or write [81, 130]. As a result, we still lack a holistic picture of how students engage with ChatGPT as part of their broader learning workflows.

Against this backdrop we ask:

RQ1a: What categories of ChatGPT prompts do students employ on a daily basis?

Given the challenge of phrasing effective prompts [26, 40, 49, 134] and repairing user-ChatGPT conversations [23, 111, 134], we ask:

RQ1b: What are the main challenges of interacting with ChatGPT faced by students in theri daily use? How do students resolve these challenges?

Beyond describing what students ask of ChatGPT and how they troubleshoot conversational breakdowns, we also aim to understand which learners remain invested in the tool as the semester unfolds. Learning-analytics research has shown that the first few interactions a student has with an online system can foreshadow later outcomes; by converting raw click streams into time-lagged behavioral features, scholars have predicted course completion, grade trajectories, and dropout risk [1, 25, 29, 69, 88]. These successes suggest that early ChatGPT usage patterns—such as the variety of prompt categories or the frequency of self-repairs—might likewise signal whether the chatbot becomes a lasting part of a student's learning repertoire. If so, timely feedback could help instructors encourage productive habits or intervene when reliance appears unbalanced. Building on this premise, we pose the following question:

RQ2a: Which usage patterns correlate with continued or increased reliance on ChatGPT over time?

Although our focus is on predictors of sustained engagement, work on technology non-use reminds us that disengagement is equally revealing. Survival-analysis approaches such as the Cox proportional hazards model have traced abandonment trajectories for social media, medical

sensors, and other technologies, uncovering contextual factors that push users away [17, 47, 75, 116]. Adapting these models to educational AI allows us to ask:

RQ2b: Which usage patterns indicate a likelihood of continued, long-term use of ChatGPT by students?

To address these research questions, we draw upon three interrelated theoretical frameworks: First, Self-Directed Learning (SDL) offers a lens for understanding how students take initiative, set goals, and manage their own learning processes—especially in informal and technology-mediated environments [82, 122]. ChatGPT, with its capacity for on-demand support and adaptive interaction, serves as a novel context for SDL in higher education[16, 84].

Second, Uses and Gratifications Theory (UGT) helps explain students' motivations for adopting and continually engaging with ChatGPT [44, 66]. Students may seek utilitarian benefits (e.g., task completion), hedonic experiences (e.g., enjoyment), technological novelty, or social gratification (e.g., feeling supported or understood), revealing the multidimensional reasons behind sustained use [93, 131]. However, misalignment with user expectations might negatively affect sustained technological use. This is especially true for AI technologies where limitations might not be clear to users [87]. When breakdowns occur at points of misalignment, users have to engage in communication repair with technology [10]. The success of these repairs is important in determining long term use [52].

Third, we draw on Human-Computer Interaction (HCI) scholarship that explores the emotional and relational dimensions of chatbot use. Emotions [96] and parasocial relationships [90] shape how students develop trust in, depend on, and emotionally engage with AI systems. Building on this, we also incorporate empirical studies on ChatGPT use in educational settings, including recent frameworks that classify different types of user dissatisfaction [72].

This triangulated approach—drawing from Self-Directed Learning, Uses and Gratifications Theory, and Human-Computer Interaction —offers a richer understanding of how students appropriate ChatGPT not merely as a cognitive tool, but as a technological companion embedded within their learning ecosystems. As a socio-technical partner, ChatGPT must balance usefulness, emotional support, and adaptive dialogue to meet students' evolving needs. Building on this theoretical framing, we present findings from a mixed-methods study analyzing naturalistic interaction logs from 36 undergraduate students. These logs capture a wide range of self-initiated uses of ChatGPT across academic, professional, and personal contexts. Our analysis reveals how students engage with ChatGPT to co-regulate their learning—seeking information, generating content, managing system ambiguity, expressing emotion, and reflecting on their progress. By identifying usage patterns linked to sustained engagement and examining students' strategies for adapting to system limitations and conversational breakdowns, we provide a grounded account of AI-mediated learning in everyday practice. These insights culminate in design and policy recommendations for integrating generative AI in higher education in ways that foreground transparency, foster resilience, and support self-directed learning.

2 Related Work

The growing presence of ChatGPT in academic settings has sparked multidisciplinary interest in how students engage with generative AI tools. In this section, we synthesize related work across three key strands of literature that inform our study. First, we examine how ChatGPT is reshaping SDL in higher education, especially in informal, technology-mediated contexts. Second, we draw on UGT to understand student motivations and strategies for managing risk, trust, and ambiguity when interacting with AI. Third, we draw from Human-Computer Interaction literature to explore the emotional and relational dynamics of chatbot use, emphasizing how these affect engagement

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and trust. Together, these threads establish the conceptual foundation for our analysis of how students incorporate ChatGPT into their daily learning routines.

2.1 ChatGPT and Self-Directed Learning in Higher Education

SDL is the learner-driven process of setting learning goals, identifying resources, applying strategies, and evaluating outcomes [77]. With the advent of digital platforms such as YouTube, MOOCs, and Duolingo, SDL has expanded beyond formal education to include informal, technology-enabled learning across diverse digital contexts [98, 124]. Advances in ICT and AI—particularly tools like ChatGPT—have transformed SDL into an increasingly dynamic and interactive process [37, 82].

Effective interactive learning environments (ILEs) should extend SDL by enabling students to plan, monitor, and reflect on their learning experiences [7, 34, 108, 120]. Within this evolving landscape, ChatGPT emerges not merely as a tool but as a contextual force that shapes how learners manage emotional, cognitive, and procedural demands. The affordances of ILEs, as identified by Self [118] and Nwana [97], are central to understanding how AI tools support SDL. These include:

- (1) Corrective identifying and repairing learner misconceptions;
- (2) Elaborative addressing knowledge gaps and introducing new material;
- (3) Strategic adjusting instructional tactics when other interventions fall short;
- (4) Diagnostic assessing learners' conditions and competencies;
- (5) Predictive using learner data to anticipate outcomes and guide actions;
- (6) Evaluative measuring learner progress and system effectiveness.

ChatGPT exemplifies this transformation by providing personalized, adaptive learning support. It promotes learner autonomy while simultaneously raising concerns around over-reliance, bias, and data privacy [84, 85]. Building on Song and Hill's SDL model—which highlights the interplay among personal attributes, self-regulation, and learning context [122]—Li et al. include AI-specific factors such as technology readiness, adaptability, and socio-technical dynamics [82]. These factors affect the motivation of users to continue using a technology, a dynamic articulated in the uses and gratifications theory presented below.

2.2 Uses, Gratifications, and Uncertainty in ChatGPT Adoption

In this subsection, we explore how students' motivations for using ChatGPT and their responses to its limitations can be understood through the dual lenses of Uses and Gratifications Theory (UGT). We begin by outlining how students' utilitarian, hedonic, and social goals drive adoption and shape sustained use of ChatGPT. We then examine how perceived ambiguities—such as mistrust in output accuracy or lack of system transparency—lead students to communication breakdown management.

- 2.2.1 Uses and Gratifications. Uses and Gratifications Theory (UGT) provides a lens for understanding why students turn to a specific technology in this case ChatGPT. UGT emphasizes user motivations for using different technologies [30]. For students, ChatGPT can deliver: (1) Utilitarian Gratification: Efficiency in completing academic tasks, such as writing and coding [22]; (2) Hedonic Gratification: Enjoyment and playfulness in interacting with a conversational agent [6, 67]; (3) Social Gratification: Opportunities for social interaction or perceived companionship, especially through parasocial dynamics [90, 131]; and finally, (4) generative AI can amplify their creative co-production [86].
- 2.2.2 Mental Models of ChatGPT. When engaging with complex technical systems, users often develop simplified mental models or folk theories—abstract representations of the underlying technology—that help them interpret and navigate system behaviors that would otherwise seem

opaque [42, 48, 68, 70]. For example, undergraduate students — see internet as a "huge information resource," without a conception of the underlying physical and firmware infrastructure [137].

When user mental models are not in line with way a technology actually works, this creates confusion — especially with newer technologies when users do not have a strong sense of their limitations [33, 41, 43], and specifically when used to teach complex concepts [57, 63, 109]. This is especially true because ChatGPT might lack the sensitivity to maintain what students see as meaningful interactions [43]. However, earlier work shows that systems that provide explanations for interactions allow students to build better mental models. We explore ChatGPT limitations and user repair strategies next.

2.2.3 Misalignment Between User Goals and Technology Output. Kim et al [72] described a taxonomy of user dissatisfaction with ChatGPT, drawing from a wide range of empirical and conceptual studies. At the core is the issue of intent understanding—users often report that ChatGPT misinterprets their goals or ignores specific contextual cues, leading to misaligned outputs [105]. This dissatisfaction is compounded when the assistant fails to match the expected communication tone [107]. In addition, refusal to answer, particularly when accompanied by safety disclaimers—can be perceived as obstructive, especially when users seek neutral or academic engagement with controversial topics [15, 21, 55]. Earlier work showed that one major concern is the depth and originality of content produced by the assistants. Users express disappointment when responses are too vague [21], insufficiently novel [76], or lack substantive detail [78]. This aligns with broader critiques that LLMs often generate surface-level answers unless carefully prompted. Information accuracy has emerged as a particularly urgent issue. Users have flagged factual errors [11], outdated knowledge [101, 133], internal inconsistencies [3], and illogical reasoning [28] as major sources of frustration. Some responses include unverifiable or fabricated details, known as hallucinations [64], while others overly agree with user input—engage in sycophancy [102, 103].

Users actively seek cues, feedback, and experiences to reduce ambiguity and establish trust when engaging with unfamiliar digital tools such as AI-driven systems like ChatGPT [87]. When students experience ambiguity about the AI assistant's credibility or trust, their interactions with the system (e.g., experimenting with AI prompts)serve as a repair mechanism for communication breakdown [8, 87, 101, 123]. On the system's side, Ashktorab et al. showed how providing the user with options was the most helpful repair strategy since it allows the user to "narrow down" the tasks that the bot *can* do, while also introducing more "clutter" into the conversation [10].

This all suggests a nuanced interplay where students seek out ChatGPT for specific benefits (e.g., information access and content generation) while also managing system limitations. This study addresses what behaviors increase use and commitment over time.

2.3 Human-Chatbot Interaction: Emotional and Cognitive Dimensions

Research in Human-Computer Interaction provides additional context for understanding how students relate to ChatGPT. Studies show that while chatbots can simulate human-like conversations, they often fall short in understanding nuance, leading to frustration or distrust [24, 89]. Users adopt various coping strategies (e.g., rephrasing prompts) or fall prey to automation bias, accepting incorrect responses based on prior positive experiences [83, 135].

Emotions play a central role in these interactions. Negative emotions like confusion can prompt users to abandon the chatbot, while empathetic responses enhance engagement [45]. Emotional regulation features, such as mood recognition, suggest that AI chatbots may also serve affective functions, extending their utility into areas like mental health and stress management [95].

Furthermore, parasocial relationships—where users perceive chatbots as social actors—are increasingly common, particularly among students seeking companionship or cognitive offloading

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[90]. Although these interactions are one-sided, they can influence how students trust, rely on, and emotionally respond to AI systems.

Students engage with ChatGPT for a wide range of academic tasks, from writing and language learning to programming and research support [58, 74]. Surveys also report that students use it for personal decisions, indicating the tool's growing role in both academic and non-academic contexts [66, 127]. However, much of the current research relies on self-reporting, leaving a gap in understanding actual behaviors and longitudinal use patterns.

Our study addresses this gap by analyzing direct interaction logs and combining them with mixed-methods insights. This approach captures how ChatGPT functions as a site of self-directed learning, how students' expectations and needs (as described by UGT in Section 2.2.1) align or clash with their experiences, and how they manage ambiguities surrounding AI use (as informed by limitations in Section 2.2.3).

Instead of limiting ChatGPT to the role of a cognitive tool, we frame it as a socio-technical actor that co-constructs students' learning experiences—shaping, and being shaped by their goals, strategies, and affective responses.

3 Dataset

Our dataset comprises chat histories from undergraduate students at a research university in the northeastern United States. We recruited participants through on-campus flyers and offered a \$10 compensation for their participation. The data collection process occurred in two waves: an initial group of 12 users in October 2023, followed by an additional 24 users in January 2024, resulting in a total sample of 36 undergraduate students.

Participants were instructed to export their complete chat history from chat.openai.com and upload the resulting zip file to our secure website. The donated data encompassed all historical conversations between the participants and ChatGPT. To ensure participant privacy and data security, we implemented a rigorous anonymization process. Though the chat logs themselves do not explicitly contain links to personal information such as email addresses or phone numbers, the content of the conversations could potentially reveal aspects of a participant's identity. To mitigate this risk, we removed all identifiable user information during the data cleaning process. Furthermore, we did not collect any demographic information, and there is no way to connect a specific chat log to the individual who donated it, as all identifying links were removed or anonymized. The final dataset is structured as follows: (1) User ID: (it's more like the documentation name, not identifiable online, non-related to students' real ID); (2) Title (like the conversation themes, automatically generated by ChatGPT); (3) Conversation ID (one conversation can have one to multiple user entries and ChatGPT's responses); (4) Create Time; (5) User Text; and (6) ChatGPT Text.

Some details of the data are shown in Table 1. Our dataset spans over a year of activity from December, 2022 to Jan, 2024, with an average of 45 sessions per user (standard deviation 66). The average session duration was 13 minutes. Figure 1 shows the timeseries of conversations in our dataset. The dataset follows school patterns closely, with reduced activity during Spring break (March), summer and during holidays in December.

Table 1. Dataset details.

# Users	# Unique Chats	# Messages	Mean Session Duration	Period of coverage
36	1,631	10,536	13.2 minutes	Dec 2022 - Jan 2024

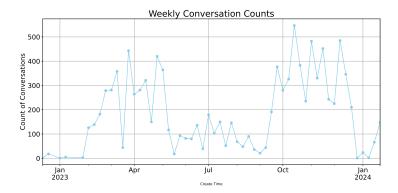


Fig. 1. Timeseries of the conversations in our dataset. We can clearly see decreased activity during Spring break (March 9-17) and Summer 2023 indicating that most usage was academic.

4 Methods

In this section, we detail the mixed-methods approach used to examine student interactions with ChatGPT. We begin with a qualitative coding process, describing how inductive analysis of user–AI conversations informed the development of a comprehensive codebook. Next, we explain how these codes were used to automate large-scale labeling via GPT-40, enabling full annotation of over 10,000 prompts. We then present our temporal analyses, including lagged regression modeling to assess how past behaviors predict future engagement, and a Cox Proportional Hazards model to examine how different usage categories relate to long-term retention. Together, these methods offer a rigorous, multi-layered perspective on student use patterns, motivations, and learning outcomes.

4.1 Qualitative Coding

We conducted an inductive qualitative analysis of the dataset, examining both student inputs and ChatGPT responses to identify themes and categories [31]. Using NVivo, we coded each message—student or ChatGPT—as the unit of analysis. While logs were organized by source, we coded across user-AI boundaries to capture thematic continuity [31].

Guided by grounded theory [51], we used open coding to identify emergent patterns, followed by axial coding to organize them into meaningful categories.

Given the dataset's volume, full coding was infeasible. We began with logs from the first 12 students, hand-coding 1,882 messages to develop a preliminary codebook.

To broaden analysis and reach thematic saturation, we used purposive sampling on the remaining 24 students in two rounds [35, 53]. First, we randomly coded 10 conversations per student, revealing frequent patterns. Then, we sampled up to 20 conversations per quartile based on interaction length and title-change frequency to capture diverse behaviors. No new codes emerged, confirming saturation [53].

Two authors collaboratively coded the initial sample, developing a multi-level codebook with examples and notes. Differences were resolved through comparison and discussion. Regular meetings ensured consensus, consistent with qualitative research standards that prioritize coder agreement over inter-rater reliability [91].

The final scheme includes five primary categories: Content Generation (GA), Information Seeking (IC), Language Use (LU), Student–ChatGPT Interaction (SC), and ChatGPT Response Behavior (CR). The first three reflect functional use, the latter two capture relational dynamics. Sub-codes are detailed in Appendix A.

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(1) **Information Seeking**: This category involves retrieving factual information, clarifying concepts, or answering specific questions. Students sought help on academic topics, job applications, medical issues, and social or cultural matters, reflecting everyday information needs [114].

- (2) **Content Generation**: This category covers the creation of original content such as essays, code, poems, and resumes. Prompts varied across academic subjects, job applications, and brainstorming tasks, emphasizing creativity and stylistic input.
- (3) **Student–ChatGPT Interaction**: This category captures socially meaningful engagement with ChatGPT—follow-up questions, emotional responses, and signs of treating the AI as a conversational partner. A rare subset (1%) included role-play and fictional dialogues.
- (4) **ChatGPT Response Behavior**: This category focuses on how ChatGPT responds to students, especially in problematic or unsatisfying interactions [106], such as when it misinterprets prompts or adjusts its response style and complexity.
- (5) **Language Use**: This category includes paraphrasing, synonym/antonym suggestions, rhetorical style adjustments, grammar checks, and translation—tasks where students provided text and ChatGPT refined it.

4.2 Automated labeling of commands using GPT and relying on the qualitative codebook

Our dataset contains 10.5k instances, making automation essential for labeling. We also aimed to capture the model's chain-of-thought (CoT) reasoning to better understand its labeling rationale [128]. Following Chae and Davidson's guidance for large datasets with limited annotations [27, P.45], we used a few-shot prompting strategy, incorporating command and subcommand descriptions along with labeled examples.

We used OpenAI's GPT-40 model (gpt-40-2024-08-06), which offers improved reasoning and coding capabilities [99], to label the full dataset via the OpenAI API. Our procedure included:

- (1) Constructing the Prompt and Feeding the Codebook to GPT:
 - We designed the prompt to ensure clear labeling, categorization, and CoT reasoning. The full codebook, including categories and examples, was provided to GPT for context [14]. The prompt specified:
 - "The following are codes for qualitative analysis. You need to categorize the texts in inputs as one or multiple codes from the following list and also reply with your chain of thought (COT) for the selection(s)." "Reply with **only the label in single quotation**, and then include COT in the next line without quotation. Remember, you are bound by only 1 label to reply."
- (2) Labeling the rest of the dataset: Using this prompt, we applied our codebook by assigning sub-categories under their respective top-level categories. For instance, under the Information Seeking category, the model labeled sub-categories such as "Multiple Choice/Fill-in-the-Blank" (typically under the Content Generation category) or detected user emotions like "Frustration/Dissatisfaction" (typically under the Student-ChatGPT Interaction category). Having refined the labeling process, we used the OpenAI API to run the model on our entire dataset. This resulted in five main categories and 41 sub-categories.
- (3) Interrator reliability for main categories: We sampled 100 prompts for each main category, with one author coding the top-level category. Interrater reliability was assessed using Cohen's Kappa [92]. As shown in Table 2, results indicated substantial to near-perfect agreement: 0.81 (Information Seeking), 0.85 (Content Generation), 0.83 (Student-ChatGPT Interaction), 0.75 (ChatGPT Response Behavior), and 0.91 (Language Use). Given our observed kappa scores, this aligns with Chae and Davidson's [27] finding that large language models,

- when guided by a few illustrative examples and a clear coding schema, can achieve moderate to substantial agreement with human coders.
- (4) **Identifying broader patterns**: We conducted a follow-up round of qualitative coding to explore how discourse unfolded within and across the five main categories. Through axial coding [126], we analyzed interaction data to identify new concepts and relationships, revealing overlapping themes and subtle transitions between sub-categories (similar to methodology presented in [5]). This analysis enriched our understanding of each category's internal structure and supported more detailed, conceptually grounded descriptions.

Category	Kappa Score	
Information Seeking	0.81	
Content Generation	0.85	
Student-ChatGPT Interaction	0.83	
ChatGPT Response Behavior	0.75	
Language Use	0.91	

Table 2. Cohen's Kappa Scores Across Annotation Categories

Accomplishing these analytic steps in sequence enabled us to follow the mixed-methods model proposed by Aranda et al. [9], which integrates computational and qualitative approaches to critically analyze large-scale textual data. Specifically, by using axial coding to refine our sub-categories and examine intersections among the main categories, we aligned with their transformative design that combines depth of interpretation with systematic structure discovery, thus advancing a context-sensitive discourse analysis grounded in both theory and data.

4.3 Temporal Analysis

We developed a feature set to support regression models analyzing how sentiment valence and prompt subcategory relate to future engagement with ChatGPT. This included 41 use categories derived from qualitative coding of prompt sub-categories (see §4.1). Additionally, we incorporated two control features: sentiment metrics generated using the VADER tool which provides a composite valence score for each prompt [62], and the length of each user prompt.

4.3.1 Effect of Recent Use History on Future Use. Earlier work used lagged linear regression to detect future effects of drugs on patients from electronic health record data [124]. An application of this model was presented in [20] and [117].

We defined weekly session length as the number of interactions per student per week. To account for temporal dynamics, we created lagged versions of each feature (presented in §??), reflecting their values in the previous week. Only students with at least two weeks of data were included after applying .groupby().shift(1) to compute these lags. The final model was a linear regression, using the lagged feature set as independent variables and the following week's session length as the dependent variable. Standardization was applied to the predictors using StandardScaler.

The model achieved an R² of 0.79 and an MSE of 250.45, indicating strong explanatory power and relatively low prediction error.

4.3.2 Survival Analysis. We used a Cox Proportional Hazards (PH) model [36] to examine how ChatGPT usage behaviors predict time to disengagement. This semi-parametric model estimates the hazard function h(t) without assuming a specific outcome distribution. The baseline hazard $h_0(t)$ is shared across individuals, and regression coefficients indicate each covariate's effect on weekly

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ChatGPT Usage by Category: Counts and Percentages

Information Seeking (3,655 / 33.4%) Student-ChatGPT Interaction (1,057 / 9.7%) Language Use (749 / 6.9%) Content Generation (3,061 / 28.0%)

Fig. 2. Breakdown of log interactions based on the five top categories.

non-use risk. Exponentiated coefficients, $\exp(\beta)$, reflect relative risk: values <1 imply reduced risk of non-use; values >1 imply increased risk.

Implemented via lifelines' CoxPHFitter in Python [38], the model used time-to-disengagement (in weeks) and a binary disengagement flag. All 34 observations were uncensored. After removing collinear variables, the final model included 23 covariates from coded usage data. Baseline hazards were estimated using the Breslow method.

The model achieved a concordance index of 0.90, indicating strong predictive accuracy. The partial log-likelihood was -67.97, and the log-likelihood ratio test was 41.21 (23 df, $-\log 2(p) = 6.48$), confirming the covariates' joint significance. This survival analysis offers interpretable insights into how usage patterns shape long-term ChatGPT engagement.

5 Findings

In this section, we present our main findings around five themes - information seeking; content generation; language use, student-AI interaction, and ChatGPT response behavior. The overall breakdown is presented in Figure 2.

5.1 Information Seeking

Our respondents used ChatGPT to retrieve factual information (e.g., what is the GDP per capita of the US?), clarify concepts (e.g., explain what the term structuration means in Sociology?), and ask ChatGPT to answer specific questions (e.g., multiple choice questions). These include academic content, medical information, and social/cultural issues of the day thus satisfying students' everyday information needs [114]. Figure 3 shows the breakdown (by percentage) prompt subcategories.

5.1.1 Academic Information Seeking. Most of the information seeking commands were focused on academic content. These spanned different academic fields: (1) STEM fields; (2) social science; and (3) humanities.

In STEM fields like mathematics, statistics, and computer science, students used ChatGPT more for problem-solving, coding assistance, and clarifying some concepts and methods, valuing its precision and logical reasoning, and application capabilities. A substantial portion of these

ChatGPT Response Behavior (2,411 / 22.1%)

interactions involved **concept explanation** (23%), where students sought foundational definitions such as "what is IEEE floating point format." Another common pattern was **practical coding or technical help** (14.9%), in which students asked for debugging and output clarification, e.g., "what does malloc do and why do I need it?" These were complemented by **clarification of syntax or programming semantics** (13%), where students asked detailed questions about code structure or behavior, such as "const int *iptr vs int *const iptr."

Students also engaged in **theory application** (11%), where they applied learned formulas or reasoning steps to novel problems. For instance, one student requested help with the question, "What is the probability that at least 1 error is made?" or asked for clarification on solutions, such as "Can you go over this solution: P(A|B) = P(A)P(B|A) = .36 = 36?" These explanations reinforced analytical thinking and comprehension of formal methods. For topics such as coding and mathematical problem-solving, students tended to engage in longer, more detailed interactions. These conversations often included multiple exchanges, where students asked follow-up questions or requested clarifications. For instance, when a student received a response on a mathematical equation, they followed up with, "Wouldn't it make more sense to write it as … [mathematical equation differing from ChatGPT's answer]." This iterative dialogue allowed students to refine their understanding and receive further targeted guidance through problem-solving steps tailored to their specific needs. These interactions frequently reflected **process explanation or workflow help** (7%), as students worked through step-by-step instructions or logical sequences.

Moreover, students asked ChatGPT to help **interpret data**, **graphs**, **or outputs** (8%)—particularly in statistics or computational assignments. Examples include questions like "*Interpret a z-value of 0.93*" or "*What can we say about the p-value given d* = 100?" These indicate students' attempts to make sense of empirical findings or statistical significance.

In social science fields, students engaged with ChatGPT to explore theoretical frameworks, social trends, and case study analysis, appreciating its adaptability in addressing multifaceted and context-dependent questions. For example, one student explored "Cultural and technological events significant to the development of video games" to evaluate how societal and technological changes have shaped the gaming industry. These interactions aligned with real-life examples or analogies (5%), as students used comparisons or narratives to deepen their conceptual understanding. Students also turned to comparison or contrast (8.3%) questions, such as "What's the difference between misinformation and disinformation?," to delineate social science concepts in clear terms. These interactions allowed students to assess the social impacts and consequences of historical and contemporary phenomena within specific contexts. Another example is when a student asked, "Did slavery and racial prejudice gradually evolve in Virginia during the half century following the arrival of the Angolans, or did de facto enslavement of Africans begin in 1619?"

Students used ChatGPT to clarify theoretical humanities concepts, though they focused more on the connection and comparison between different theories and concepts instead of seeking clarification for just one concept. For example, one student asked, "Explain the importance of truth as Nietzsche connects it to the figure of Socrates in The Birth of Tragedy." These deeper discussions often reflected both validation or evaluation of understanding (4%) and exploratory comparison. In some cases, learners also sought clarification of assignment prompts or criteria—classified under clarification of instructions or tasks (2%)—e.g., "Should I reverse the alternative hypothesis?" or "Can the alternative hypothesis be about lower means instead of higher?"

Taken together, these ten subcategories of academic information seeking represent a complex and rich interaction between students and ChatGPT, ranging from foundational conceptual support to advanced application and reflective validation.

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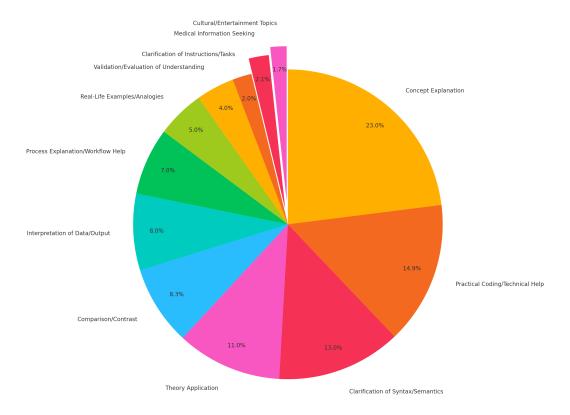


Fig. 3. Information seeking breakdown

5.1.2 Medical Information Seeking. While lower than academic information access (at 2.1%), students also asked for the causes and general advice on improving their mental or physical health. For example, one student asked "Can period cramps cause sciatic nerve pain? How can I help lessen this pain?". Another case was that one student asked "how can I quickly stop the bleeding if I cut my finger?" Students also sought clarification on specific treatments, such as "Is notebook therapy legit?". Additionally, students used ChatGPT to explore medical history, including the origins and evolution of significant diseases. One student questioned the geological origin of COVID-19, "did covid-19 start in China?", where ChatGPT provided contextual information about the pandemic's emergence and its global impact.

5.1.3 Cultural or Entertainment Topics. Finally, students discussed social and cultural issues of the day like social movements of specific historical periods (e.g., BLM or social rights movement), historical perspectives on current political and military debates, and geographic disputes, religious customs, and cultural practices as well as questions about broadcast media.

5.2 Content Generation

While information seeking showed how students used ChatGPT more in-line with how a search engine can be used, we describe the use of ChatGPT for content generation in this section, where

students used ChatGPT to create original or structured content such as essays, explanations, outlines, code, resumes, emails, and academic writing. The breakdown is presented in Figure 4.

5.2.1 Academic and Professional Content Generation. Students actively engaged ChatGPT to generate both academic and practical content, reflecting diverse needs and strategies for learning, productivity, and communication. These uses ranged from answering structured questions to producing job application materials.

The most frequent type of content generation was the use of ChatGPT for **multiple choice and fill-in-the-blank questions** (30.8%). Students submitted quiz-style items from homework or exams and asked ChatGPT to select the correct answer or complete a missing statement. These requests were often quick and transactional, emphasizing factual recall and brief verification. Occasionally, students followed up by asking for a brief justification, revealing that correctness and reasoning were both valued.

The next most common category was the request for **examples** (15%), which students used to understand abstract principles. For instance, prompts like "Give me an example of how recursion is used in sorting algorithms" were used to ground theoretical content in real-world or computational scenarios. These examples spanned disciplines, with particular emphasis on computing and social sciences.

Computer science coding (11%) was another major use case. Students asked ChatGPT to write functions or scripts in languages like Python or JavaScript. These requests were often iterative: students began with natural language descriptions or pseudocode, received output, and then followed up to troubleshoot or refine the result. For example, a session might begin with, "Write a Python function to check if a string is a palindrome," and continue with, "Why is this giving me an index error?"

Summarization (8%) and **explanation** (6%) tasks helped students better understand lecture content or difficult concepts. Summarization prompts like "Summarize this article on stochastic gradient descent" allowed students to condense information for review, while explanation prompts such as "Explain the chain rule in multivariable calculus" revealed a desire for more accessible breakdowns of complex material.

Students also requested **step-by-step solutions** (6%), especially in STEM fields, as a way to validate or supplement their own problem-solving approaches—e.g., "Solve this integral step by step." Similarly, **editing and writing improvement** (5%) requests targeted clarity, tone, or argument structure in essays and written assignments, while **outline generation** (4%) assisted students in organizing ideas before drafting. Across these sub-categories, a common thread is the use of ChatGPT as a collaborative thinking partner to brainstorm, scaffold and refine ideas especially in early-stage work.

Students also asked for **definitions** (3%) and **comparisons** (3%) to support academic argumentation, such as "*Define utilitarianism*" or "*Compare Locke and Hobbes on political authority*." These helped refine conceptual understanding and analytical framing.

Smaller but meaningful categories included **academic citation requests** (2%)—such as formatting sources in APA or MLA—and **email or letter generation** (3%), where students requested help composing professional correspondence (e.g., "Can you write an email to request a deadline extension?").

Finally, **job application content generation** (5%) captured a distinct set of prompts where students asked ChatGPT to create resumes, cover letters, or responses to interview questions. Students often supplied raw experience details and asked for polished output tailored to specific roles—e.g., "Turn this paragraph into bullet points for a resume." These sessions illustrate how ChatGPT was used to scaffold high-stakes professional writing.

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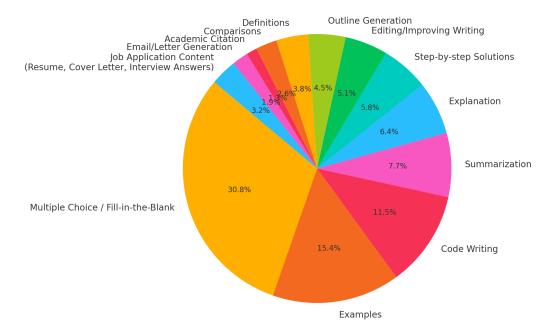


Fig. 4. Content generation breakdown

Together, these patterns demonstrate that students viewed ChatGPT as a flexible tool—one that could serve pedagogical, creative, and professional functions, often within the same workflow.

5.3 Language Use

The Language Use category captured student interactions aimed at improving the form, tone, and clarity of existing text, rather than generating new content or seeking information. Students frequently engaged ChatGPT as a language enhancer—rewording text, checking grammar, translating content, and refining rhetorical elements to align with academic and communicative norms. The breakdown of the language use category is presented in Figure 5.

A prominent theme was rewording, where students asked ChatGPT to rephrase sentences, paragraphs, or full drafts to improve clarity, shift tone, or reduce redundancy. Prompts included directives such as, "Rephrase this to sound more academic," or "Make this simpler without changing the meaning." These requests reflected a desire for stylistic precision and sometimes served as safeguards against unintentional plagiarism.

Grammar checking was another central use. Students submitted passages for correction and often sought explanations for the changes, using ChatGPT as both editor and tutor. For example, one might ask, "Fix the grammar in this paragraph," followed by, "Why is it 'has been' instead of 'was'?" In doing so, students practiced rule-based learning while enhancing the fluency of their writing.

Some students extended this refinement process into rhetorical support, requesting help with persuasive techniques and stylistic strategies. ChatGPT was asked to generate examples of rhetorical devices—like analogies, metaphors, or parallel structure—or to assess the argumentative strength of a draft. These requests positioned ChatGPT as a coach for enhancing persuasive impact.

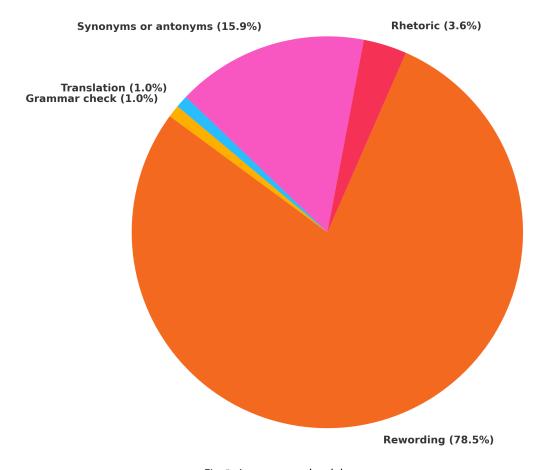


Fig. 5. Language use breakdown

Requests for synonyms and antonyms were also common. Students used these to diversify vocabulary, adjust tone, or elevate the sophistication of their language. For instance, a student might ask, "What's a more formal word for 'get'?" or "What's the opposite of 'optimistic'?"

Lastly, translation tasks, though less frequent, reflected the multilingual context of many learners. Students requested translations not just between English and other languages (often Chinese), but also asked for cultural and idiomatic clarification—e.g., "What's the best way to say this in a formal Chinese email?" These interactions reveal students' attention to both linguistic accuracy and communicative appropriateness across cultural contexts.

Taken together, these behaviors demonstrate that students viewed ChatGPT not only as a generative tool but also as a linguistic partner—helping them refine, polish, and professionalize their writing through a combination of stylistic assistance, language learning, and rhetorical support.

5.4 Student-ChatGPT Interaction

Beyond seeking information and generating content, students interacted with ChatGPT in ways that revealed deeper emotional and reflective engagement. In this section, we explore the affective and meta-cognitive dimensions of these interactions, examining how students used ChatGPT not

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only as a tool for completing tasks but also as a space for expressing ambiguity, tracking their learning progress, and managing their emotional experiences. We describe patterns of confusion and frustration, expressions of gratitude and confidence, and behaviors like follow-up questions, prompt revisions, and even humorous or human-like exchanges with the assistant. These behaviors underscore ChatGPT's evolving role as both an educational support system and a conversational partner in students' learning ecosystems. The breakdown of subcategories for Student-AI interaction is presented in Figure 6.

5.4.1 Affective and Meta-Cognitive Interaction with ChatGPT. In addition to information seeking and content generation, students demonstrated a variety of affective and meta-cognitive behaviors while using ChatGPT. These interactions reveal not only how students used the tool but also how they monitored their learning, expressed confidence or frustration, and sought emotional reassurance.

The most common theme was **expression of uncertainty or confusion** (22%). Students frequently indicated they were unsure about a topic, question, or prior answer, using phrases like "I'm not sure if this is correct" or "Can you double-check this for me?" These expressions reflect both vulnerability and a desire for cognitive confirmation, positioning ChatGPT as a judgment-free feedback mechanism.

Self-reflection and learning awareness (18%) also emerged prominently. Students acknowledged their progress or difficulties, saying things like "I think I understand it better now" or "I need to work on these kinds of problems more." These statements show that ChatGPT facilitated metacognitive evaluation and promoted learner self-assessment.

Students frequently engaged in **follow-up or clarification requests** (16%), using the dialogue format to iterate on answers—e.g., "Can you explain that last part in simpler terms?" or "What if the input changes?" These exchanges reflect active knowledge construction and an expectation of adaptive feedback.

A newly identified theme was **interaction repair or prompt revision** (6%). When ChatGPT delivered incorrect or confusing responses, students often revised their original prompt to guide the assistant more effectively. This behavior included simplifications, restatements, or explicitly signaling the nature of the task—e.g., "You didn't follow the last sentence. Let me rephrase." or "This is a coding question. Try to be accurate." These interactions illustrate how students adapted their prompting strategies to recover from breakdowns, highlighting a form of meta-communication that supports co-regulation of dialogue.

Positive emotional exchanges such as **appreciation and gratitude** (12%) also occurred often. Students used affirmations like "*Thanks, that really helped*" to signal satisfaction, while **frustration or dissatisfaction** (10%) surfaced when ChatGPT failed to meet expectations—e.g., "*This doesn't help*" or "*That's not the right answer*."

Other forms of interaction included **confidence assessments** (8%), where students evaluated their understanding after working through a problem. For instance, after reviewing a mathematical explanation, one student remarked, "*Okay, I think I got it now*," while another wrote, "*That actually makes sense this time*," reflecting a moment of self-assured comprehension.

Humor or anthropomorphism (6%) was also evident in interactions where students playfully treated ChatGPT as a conversational partner. Some students greeted it with lines like "Hey buddy, ready to help me suffer through stats again?" or made light-hearted comments such as "You're smarter than my professor" or "You're scaring me, GPT. This is too good." These interactions anthropomorphized the assistant, attributing personality, emotions, or social roles to it.

A smaller group used ChatGPT to **set learning goals** (5%), such as "*I want to practice derivatives today*," illustrating strategic and self-directed use of the assistant.

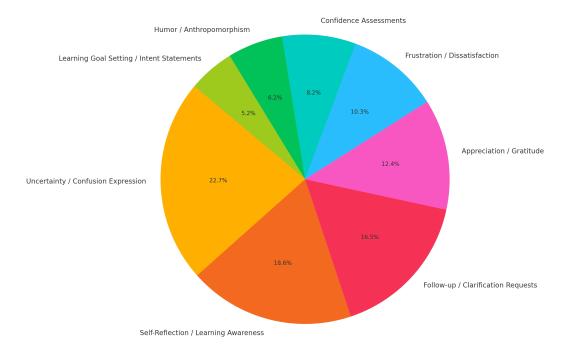


Fig. 6. Student-ChatGPT interaction breakdown

5.5 ChatGPT Response Behavior

In addition to the ways students interacted with ChatGPT, it is equally important to examine how the assistant itself contributed to the dialogic exchange. This section focuses on ChatGPT's conversational behavior—how it responded to errors, conveyed its limitations, and managed inconsistencies across interactions. By analyzing these response strategies, we gain insight into how the assistant actively participated in maintaining coherence, repairing misunderstandings, and guiding users' expectations. These patterns reveal ChatGPT as not just a source of information but as a conversational actor, performing roles of clarification, boundary-setting, and self-correction throughout its engagements with students. The breakdown of subcategories is presnted in Figure 7.

5.5.1 ChatGPT's Conversational Role and Response Strategies. This category highlights ChatGPT's role in the interaction with students, focusing on how the AI engages with users through its responses. Sub-codes in this category explore how ChatGPT adapts its language, style, and complexity to meet diverse student requests, such as ChatGPT's misunderstanding of the student prompt. Special attention is given to instances where conversational issues arise—those interactions that may be problematic or unsatisfying for the user [106].

A prominent pattern across this category is ChatGPT's use of **apologies** (39%) in response to errors, misinterpretations, or inconsistent answers. The assistant frequently begins these moments with phrases such as, "I apologize for the mistake in my previous response" or "I'm sorry for the confusion earlier." These apologies often followed contradictory answers within a session, prompting students to ask for clarification or rephrase their queries. For instance, one student noted, "Your answers are different even though the question didn't change," to which ChatGPT responded, "Apologies for the inconsistency. Let me clarify my answer." This illustrates how students actively flagged

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breakdowns in coherence, and the assistant, in turn, acknowledged the fault and attempted to recover the interaction.

Another major theme was the articulation of **ChatGPT's limitations** (32%). These were moments where the assistant clearly stated its inability to fulfill a request, often due to its lack of real-time data, inability to run code, or neutrality in subjective matters. Examples include: "I'm sorry, but I cannot access current news articles," "I'm unable to execute code," and "As an AI developed by OpenAI, I don't hold personal beliefs or values." Rather than ending the exchange, such disclaimers typically led students to rephrase their prompts, treating these limitations as cues for interactional repair. This boundary-marking behavior allowed students to recalibrate expectations and re-engage with more viable queries.

The final subcategory involved **unintended or inconsistent answers** (29%), where ChatGPT's output changed unexpectedly or contradicted prior responses. In several sessions, students directly challenged these shifts—e.g., "Didn't you just say the opposite?" or "This doesn't match what you just told me." The assistant often replied with corrective language: "I apologize if my previous message was unclear. Let me try again." These interactions revealed how users monitored ChatGPT's coherence and held it accountable for internal consistency. When the assistant's answers lacked stability, students either corrected it, expressed frustration, or tried alternative phrasings.

Taken together, these subcategories: apologies, limitations, and unintended answers show the ways ChatGPT performs conversational self-regulation. Rather than solely providing information, the assistant is engaged in managing misunderstandings and setting expectations. Its apologetic and boundary-setting language marks key moments in the student-AI relationship, often inviting collaboration or prompting correction, but sometimes signaling the limits of what this interactional partner can achieve.

5.6 Predictors of Increased Use

To investigate how prior user behavior with ChatGPT influences future engagement, we conducted a time-aware linear regression using a dataset of student interactions. Each interaction was timestamped and aggregated into weekly periods by student. We then summarized binary-coded interaction categories per student-week to construct lagged predictors of ongoing use.

Regression results (presented in Table 3) indicate that certain interaction types significantly influenced students' likelihood of returning to ChatGPT. The most substantial positive predictor was instances where ChatGPT issued an **apology** (β = 30.75, p < 0.005). This finding suggests that conversational repair—where ChatGPT acknowledges error—can help preserve engagement and reinforce the user–AI relationship.

Other positive predictors included **theory application** during information-seeking tasks (β = 17.52, p = 0.003) and **editing or improving writing** requests (β = 9.15, p < 0.005), both of which reflect goal-oriented academic use. These interactions likely contributed to ChatGPT being viewed as a useful academic partner, particularly in complex or higher-order cognitive tasks.

However, several types of interactions were negatively associated with continued use. Most notably, **interaction repair or prompt revision**—where students rephrased or corrected inputs following miscommunication—had a significant negative effect (β = -12.62, p < 0.005). Similarly, instances in which ChatGPT communicated its **limitations** (e.g., inability to complete a request) predicted lower likelihood of return (β = -12.03, p < 0.005). These results suggest that certain breakdowns in functionality or user effort to resolve confusion may have led to frustration rather than resilience.

Indeed, **frustration or dissatisfaction** from students emerged as a strong negative predictor (β = -11.93, p < 0.005), as did follow-up requests for **clarification** (β = -10.00, p = 0.002). Additionally, when students encountered **unintended or inconsistent answers**, it negatively impacted future

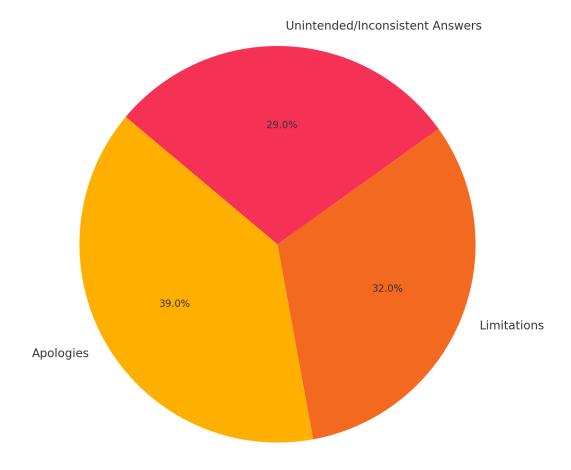


Fig. 7. ChatGPT's response behavior breakdown

use (β = -9.37, p < 0.005). These patterns suggest that disconfirming experiences—whether due to unexpected AI behavior or lack of clear response—can undermine continued engagement.

In summary, the findings illustrate a nuanced picture: while productive academic tasks and AI self-correction (via apology) support ongoing use, unresolved breakdowns, emotional discontent, and perceived AI inadequacy predict attrition. These insights emphasize that effective support, transparency, and usability are critical to fostering sustained human–AI interactions.

5.7 Who Continues to Use ChatGPT long-term

In the context of the Cox Proportional Hazards model, the hazard ratio (HR) represents the relative risk of experiencing the event—in this case, disengagement from ChatGPT—associated with a specific behavior. A hazard ratio less than 1 indicates a reduced risk, meaning the corresponding behavior is associated with a longer time to disengagement, or greater sustained engagement with ChatGPT. Significant ChatGPT usage categories are presented in Table 4.

Several usage categories exhibited particularly low hazard ratios, suggesting strong associations with continued engagement. Most notably, students who used ChatGPT to respond to unintended or inconsistent answers (HR = 0.01, p < 0.005) were significantly less likely to disengage. This

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Table 3. Top regression features predicting continued student use of ChatGPT, categorized by interaction type.

Subcategory	Main Category	β	p-value
Apologies	ChatGPT Response Behavior	30.75	< 0.005
Theory Application	Information Seeking	17.52	0.003
Editing/Improving Writing	Content Generation	9.15	< 0.005
Interaction Repair / Prompt Revision	Student-AI Interaction	-12.62	< 0.005
Limitations	ChatGPT Response Behavior	-12.03	< 0.005
Frustration / Dissatisfaction	Student-AI Interaction	-11.93	< 0.005
Unintended / Inconsistent Answers	ChatGPT Response Behavior	-9.37	< 0.005
Follow-up / Clarification Requests	Student-AI Interaction	-10.00	0.002

implies that instead of abandoning the interaction, students persisted by prompting clarifications, corrections, or trying alternative phrasings, highlighting a high level of interactional resilience.

Similarly, interactions involving job application content—such as resume bullet points, cover letters, or interview responses—also showed a very low hazard ratio (HR = 0.01, p < 0.005). This reflects how goal-oriented tasks can foster repeat engagement, as students returned to refine drafts or adapt responses to different roles.

Requests for help with multiple choice and fill-in-the-blank questions—often derived from quizzes, homework, or test preparation—also predicted sustained engagement (HR = 0.01, p = 0.01). These tasks were relatively straightforward but frequently iterative, as students would sometimes follow up to verify or justify answers.

The use of ChatGPT for code writing (HR = 0.02, p < 0.005) also strongly predicted continued use. Students prompted the assistant to write Python or JavaScript code from natural language descriptions, frequently returning with bugs, clarification requests, or updated inputs. This reflects ChatGPT's utility in supporting problem-solving loops and code debugging workflows.

Another high-engagement category was theory application (HR = 0.02, p < 0.005), where students used ChatGPT to better understand theoretical concepts (e.g., Bayesian probability). These cognitively demanding tasks likely kept students engaged by fostering deeper learning.

Additional predictors included email and letter generation (HR = 0.03, p = 0.03), which students used for drafting professional messages and outreach to instructors or employers. Meanwhile, responses to ChatGPT's limitations (HR = 0.03, p = 0.03)—such as the lackc of to access real-time data—did not deter students. Instead, they often adapted their prompts or re-engaged in revised forms.

Collectively, these findings highlight that not all interactions are equal in shaping engagement trajectories. Behaviors associated with correction, real-world relevance, and iterative work, especially when tied to academic or professional goals, predict sustained use. In contrast to assumptions that ChatGPT's errors might discourage continued use, this analysis shows that conversational breakdowns can, in fact, deepen user involvement, provided that students remain motivated to repair and refine the dialogue.

6 Discussion

This study offers a holistic, empirical view of how undergraduate students engage with ChatGPT in real-world, self-directed learning contexts. Through a mixed-methods analysis of naturalistic logs, we illuminate not only what students do with ChatGPT (RQ1a), but also the challenges they face and strategies they adopt (RQ1b), as well as the behavioral predictors of continued

Subcategory	Main Category	HR	p-value
Unintended / Inconsistent Answers	ChatGPT Response Behavior	0.01	< 0.005
Job Application Content	Content Generation	0.01	< 0.005
Multiple Choice, fill-in-the-blank	Content Generation	0.01	0.01
Code Writing	Content Generation	0.02	< 0.005
Theory Application	Information Seeking	0.02	< 0.005
Email/Letter Generation	Content Generation	0.03	0.03
Unintended/Inconsistent Answers	ChatGPT Response Behavior	0.03	0.03
Limitations	ChatGPT Response Behavior	0.03	0.03

Table 4. Top significant ChatGPT usage categories predicting longer engagement, based on hazard ratios $(\exp(\cos f))$ from the Cox Proportional Hazards Model. HR < 1 indicates reduced risk of disengagement.

engagement (RQ2a, RQ2b). In this discussion, we synthesize our findings with prior literature and theoretical frameworks to deepen our understanding of how generative AI supports, shapes, and occasionally complicates student learning. We also propose implications for future design and policy interventions.

6.1 RQ1a: Categories of Use — A Sociotechnical Learning Ecology

Students engaged ChatGPT across five dominant categories: information seeking, content generation, language refinement, affective/meta-cognitive interaction, and conversational repair. This taxonomy advances earlier work limited to specific domains (e.g., computer science education or EFL writing) by capturing a broad spectrum of daily academic and pre-professional uses [58, 73, 125]. ChatGPT emerged as a versatile "learning companion"—a "Swiss Army knife" of support—flexibly shifting between roles: explainer, tutor, writing coach, job search assistant, and emotional sounding board.

This multifunctionality reflects a convergence of gratifications consistent with Uses and Gratifications Theory, which positions users as active agents who adopt media to satisfy informational, hedonic, social, and functional needs [67, 93, 131]. Our data show that students fluidly navigated these gratifications, often within a single session. For example, a student might begin by asking ChatGPT to explain the chain rule in multivariable calculus—seeking informational gratification by filling a knowledge gap—then request a summary or code snippet to complete a task, reflecting functional gratification. Both are subtypes of utilitarian gratification, as they serve practical, goal-directed purposes.

In addition, students frequently used the assistant in ways that offered hedonic gratification, such as treating ChatGPT as a low-stakes space for experimenting with ideas or making humorous asides like "You're smarter than my professor" or "Let's suffer through stats together." These playful interactions align with prior findings that students derive enjoyment from using AI in exploratory or non-evaluative contexts [67]. Social gratification was also evident in parasocial dynamics, where students thanked ChatGPT, sought encouragement, or expressed relief ("Thanks, this really helped!")—echoing earlier studies that found users may anthropomorphize chatbots and treat them as emotionally responsive partners [90, 131].

This blending of instrumental and affective roles underscores how generative AI becomes deeply embedded in students' academic workflows and emotional routines. By fluidly transitioning between clarifying a theory, drafting a professional email, and engaging in light-hearted banter—all within a single conversational thread—students demonstrate how ChatGPT functions as a multi-gratification system that caters to the layered and shifting demands of academic life.

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6.2 RQ2a/RQ2b: Behavioral Predictors of Engagement and Retention

Our mixed-methods approach—combining lagged regression and survival analysis—offers a nuanced and empirically grounded perspective on the behavioral patterns that predict whether students continue or discontinue their use of ChatGPT over time. These findings directly address RQ2a and RQ2b, revealing that not all user behaviors have equal weight in shaping sustained engagement. Some actions deepen students' reliance on the tool, while others subtly undermine it, even when such actions may appear productive on the surface.

6.2.1 Task-Oriented Interactions as Engagement Anchors. Behaviors associated with goal-directed, academic utility—such as theory application, coding assistance, multiple-choice solving, and professional writing tasks (e.g., job applications)—consistently emerged as positive predictors of continued use. These interactions represent high-value, task-specific engagements that directly contribute to students' academic success and career preparedness.

For example, students who used ChatGPT to apply theoretical knowledge to coursework problems not only demonstrated deeper cognitive engagement (through multiple exchanges including follow-up questions or requested clarifications) but also showed stronger retention over time (see Table 4). Similarly, code writing, which often involves iterative troubleshooting, debugging, and solution refinement, appeared to foster persistent engagement by offering immediate and tangible learning benefits. This finding aligns with Self-Directed Learning theory, particularly the view that students are more likely to return to tools that help them actively construct knowledge and overcome procedural hurdles [122].

Notably, job application content generation also emerged as a strong predictor of continued use. These tasks—such as drafting resumes or tailoring cover letters—are tied to high-stakes outcomes and may reflect a growing perception of ChatGPT as a legitimate partner in students' transition to professional roles. These patterns suggest that instrumental value, when paired with perceived utility and feedback loops, becomes a key mechanism for retention.

6.2.2 Interactional Strain and Drop-Off Behaviors. In contrast, behaviors linked to interactional strain—such as prompt revision, follow-up clarification, expressions of frustration, and encounters with system limitations—were associated with reduced likelihood of return use. Although these behaviors might suggest engagement in the moment, they also signal cognitive and emotional friction in the interaction.

For example, students who frequently revised their prompts after misunderstandings or vague responses were significantly more likely to disengage over time. This highlights the cognitive toll of having to "manage" the system too often—when students must compensate for ChatGPT's lack of clarity or coherence, the perceived cost of use may begin to outweigh its benefits. Likewise, clarification requests and expressions of frustration—which on the surface suggest persistence—may instead reflect a point of diminishing returns, where students feel burdened rather than supported by the system (see Table 3).

Interestingly, while ChatGPT's expression of limitations (e.g., refusal to answer questions, lack of real-time data access) was also a negative predictor, it was not universally damaging. In some cases, when students responded adaptively—e.g., by reformulating their query or shifting goals—they continued using the tool. However, the burden of workaround often fell on the user, and when unaccompanied by system responsiveness, these interactions became demotivating.

6.2.3 Apologies and Dialogic Repair as Retention Catalysts. One of the most striking findings from the lagged regression was the positive effect of apologies issued by ChatGPT. These moments of dialogic repair—where the system acknowledged prior errors or inconsistencies—predicted

sustained use. This reinforces the idea that responsiveness and humility in AI interactions can build user trust, even when correctness is lacking.

Rather than deterring users, transparent acknowledgment of failure seems to re-establish alignment between the system and the user's expectations. In this sense, apologies are not merely politeness strategies—they are functional repair mechanisms that help restore conversational continuity and psychological safety. This mirrors theories in Human–Computer Interaction (HCI) that emphasize the role of responsive accountability in promoting user satisfaction and continued engagement [24, 89].

6.3 RQ1b: Ambiguity, Misunderstandings, and Interactional Repair

A central theme across student interactions with ChatGPT was ambiguity—both cognitive (e.g., confusion over academic content) and epistemic (e.g., mistrust in the Al's responses) [110]. Rather than abandoning the tool, students frequently responded with clarification requests, follow-ups, or revised prompts—behaviors aligned with strategies identified in prior research on conversational breakdowns with AI systems [8, 10, 23, 87].

Responsiveness Over Perfection: How Co-Regulated Dialogue Sustains Engagement in Al-Mediated Learning. Our analyses complicate the common assumption that conversational breakdowns inevitably lead to disengagement [10, 46, 136]. While interactional repair behaviors—such as prompt revisions, follow-up clarifications, and expressions of frustration—were frequently observed, our time-lagged regression reveals that these efforts were negatively associated with continued use. When students were repeatedly required to compensate for the system's limitations, the cumulative cognitive and emotional burden appeared to outweigh the benefits of persistence. In contrast, apologies issued by ChatGPT stood out as the strongest positive predictor of sustained engagement. These moments of system-led accountability restored trust and conversational continuity, underscoring that it is not infallibility, but rather responsiveness, that sustains user commitment. This finding is further supported by our survival analysis, which showed that breakdowns did not universally result in disengagement. Students who experienced inconsistent or unintended responses but persisted-through clarification or re-engagement-demonstrated interactional resilience and a lower risk of attrition. These students may have developed stronger problem-solving confidence and more refined mental models of the system, suggesting that successful navigation of ambiguity can foster deeper engagement when users are supported or sufficiently skilled to manage it.

This interplay between ambiguity and agency adds depth to earlier work on human-AI communication repair: while system ambiguity is often seen as a barrier to trust [80] and in turn reduced long-term use [12], managed ambiguity—particularly when students have the skill or motivation to recover from it—can deepen involvement and reinforce learning behaviors. Indeed, our survival model found that students who sustained their use of ChatGPT were disproportionately those engaged in cognitively demanding tasks like code writing and theoretical application. These activities may have equipped them with both the technical confidence and interactive fluency needed to persist through AI limitations. These findings echo earlier work on human-AI interactions where reciprocity [113] and equity [52] between the two parties increase the likelihood of sustained use.

Together, these findings suggest that sustained engagement with ChatGPT is not solely a function of system accuracy or student persistence. Rather, it hinges on how responsibility for conversational coherence is distributed between user and system. When students are supported—through systemled apologies, responsive clarification, or their own prior skills—they are more likely to remain engaged. Conversely, when the burden of maintaining the dialogue falls disproportionately on students, disengagement becomes more likely. In this context, fostering co-regulated dialogue—where

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both user and system actively contribute to managing communication breakdowns—emerges as a critical design goal for effective AI-mediated learning environments.

6.3.2 Co-Regulated Learning: Reframing Self-Directed Learning in Human–AI Collaboration. Across all categories of use, students were not merely passive recipients of information; they were actively managing their interactions with ChatGPT. From setting explicit goals (e.g., "I want to practice derivatives today") to expressing self-reflection (e.g., "I think I got it now") to strategically reframing prompts following misunderstandings, students engaged in co-regulated learning. These behaviors support and extend Song and Hill's model of Self-Directed Learning [122] by emphasizing the dialogic, emergent nature of AI-mediated educational engagement.

While traditional SDL frameworks have focused on individual learner traits such as motivation, discipline, and goal-setting, our findings foreground a broader set of interactional practices that scaffold learning: metacommunication, emotional self-regulation, prompt adaptation, and resilience in the face of system breakdowns [82]. Students not only adapted their strategies in response to system limitations, but ChatGPT also played an active role—modulating tone, issuing apologies, and attempting self-correction—thereby shaping the flow of learning in real time.

This bidirectional dynamic repositions ChatGPT not as a static educational tool, but as a sociotechnical partner in the learning process. Learning, in this context, becomes a jointly managed endeavor, shaped by user initiative and system responsiveness. These patterns point to the need for an updated model of SDL that explicitly incorporates AI feedback loops, affective scaffolding, and the co-authorship of learning trajectories through human–AI collaboration.

6.4 Design Implications

Our findings yield several design principles for improving generative AI in educational contexts:

- (1) **Dialogic Responsiveness as a Core Feature:** LLMs should treat follow-ups, rephrasings, and expressions of confusion as cues to shift response strategies. Systems should not only issue apologies but also meaningfully repair their mistakes—by providing clarification, flagging uncertainty, or suggesting alternatives. Apologies, in this context, should lead not merely to restatement, but to enhanced explanation or support [24].
- (2) **Persistent Context for Continuity and Trust:** Students often referred to prior turns or sessions, but ChatGPT lacked memory. Incorporating scoped conversational memory could enable coherence, reduce repetition, and improve trust [120].
- (3) **Dynamic Prompt Scaffolding and Mode Switching:** ChatGPT should detect task type and adapt its tone, verbosity, and response structure accordingly. Offering explicit modes (e.g., tutor, coach, editor) could help students set expectations and guide interactional framing [34]. In tandem, features such as prompt scaffolding, rephrasing aids, and explainable error handling can reduce the cognitive burden on students and help preserve engagement when breakdowns occur.
- (4) **Visual and Multimodal Support for STEM Learning:** Future LLMs should integrate lightweight visual aids—particularly for abstract or symbolic domains such as coding, data analysis, and mathematical concepts—where visual explanations can reduce ambiguity and enhance comprehension [7, 108].
- (5) **Built-In Metacognitive Prompts:** Given the importance of dialogic engagement between the students and ChatGPT as presented earlier, prompts such as "Did this help?", "Would you like to reflect on this answer?", or "Want to try a similar question?" can nudge students toward reflection, deepen conceptual engagement, and support the consolidation of learning [118].

6.5 Policy Implications

For educational institutions and AI developers, we offer the following recommendations:

- (1) **AI Literacy and Critical Engagement Curricula:** Students must be equipped to critically assess the accuracy of AI-generated outputs, avoid plagiarism, and navigate the uncertainties inherent in interacting with generative tools [13, 84]. Digital literacy curricula should go beyond teaching students how to craft effective prompts—they should also include strategies for recovering from breakdowns and managing failed or ambiguous interactions.
- (2) **Context-Aware "Education Mode" Features:** Instead of imposing blanket restrictions, students should receive scenario-based guidance that distinguishes between acceptable and inappropriate uses of AI in academic contexts [129]. For instance, using ChatGPT to draft a professional email is qualitatively different from generating an entire essay for a class assignment.
 - To support this, developers should integrate explainable AI for education (XAI-ED) features [71], ethical nudges [79], and metacognitive reflection prompts [104]. XAI-ED tools can help students evaluate the reliability of AI responses—particularly in ambiguous scenarios thus encouraging informed judgment. Ethical nudges, such as reminders about citation practices, originality, and data privacy, can promote responsible use and discourage academic misconduct. Metacognitive prompts like "What did you learn from this?" or "Would you like to evaluate another perspective?" can prompt critical reflection, self-assessment, and deeper engagement with the learning material.
 - Together, these features foster trust, support critical engagement, and help students maintain an active, evaluative stance in their interactions with AI. They also reinforce Self-Directed Learning (SDL) by scaffolding autonomy, ethical awareness, and reflective learning practices in alignment with educational goals [61, 122].
- (3) Teacher–Learner–Developer Collaboration: Students are already developing folk strategies and workarounds in their interactions with ChatGPT; their lived experiences should inform platform design and policy-making. Co-designing features with educators—and incorporating student perspectives—can help ensure alignment with ethical, pedagogical, and contextual values [45, 95]. As recent research has shown, fostering AI literacy is essential not only for preservice teachers, who often face technological anxieties and ethical concerns, but also for students more broadly, who express a desire for clearer institutional guidance and structured opportunities to critically engage with generative AI tools [19]. Hands-on interventions, such as targeted literacy training and scaffolded exposure to GenAI applications, can increase users' confidence, promote responsible use, and mitigate apprehension—thereby supporting more meaningful and equitable educational outcomes. These insights reinforce the importance of involving both students and educators in the design of AI systems that are not only technically effective but also socially and ethically attuned.

7 Limitations and Future Work

While our study provides a rich, log-based understanding of how undergraduate students engage with ChatGPT across academic and personal contexts, it has several limitations that suggest avenues for future inquiry. Most notably, our analysis relied entirely on analyzing interaction logs. Although this approach captures real-world use at scale, it does not include direct engagement with participants through interviews or surveys. As a result, we were unable to probe students' intentions, interpretations, or emotional states beyond what was observable in their prompts and ChatGPT's responses. This limits our ability to fully contextualize user motivations, evolving expectations, and perceptions of system trustworthiness or value over time.

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Future work should complement log analysis with qualitative methods such as in-depth interviews or diary studies, as well as quantitative instruments like surveys to triangulate behavioral findings. Furthermore, co-design sessions with students could provide an opportunity to collaboratively reinterpret usage patterns, uncover latent needs, and generate user-informed design ideas. Such participatory methods can deepen our understanding of how ChatGPT and similar tools might be better integrated into educational ecosystems in ways that align with student values, workflows, and goals.

8 Conclusion

ChatGPT is not just a technological novelty—it is a dynamic actor in students' learning journeys. Our findings reveal that students use it to seek, generate, question, reflect, adapt, and emote. Far from replacing critical thinking, ChatGPT—when properly scaffolded—can support a dialogic, emotionally resonant, and self-directed learning experience. To harness this potential, designers and educators must co-create AI ecosystems that are transparent, responsive, and pedagogically grounded.

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TBD

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A ChatGPT Codebook

A.1 Information Seeking

A.1.1 Concept Explanation. Students sought foundational definitions or explanations of key academic concepts across STEM, social science, and humanities.

Example:

"What is IEEE floating point format?"

A.1.2 Practical Coding or Technical Help. Requests focused on debugging, code output, or understanding specific programming tools.

Example:

"What does malloc do and why do I need it?"

A.1.3 Clarification of Syntax or Programming Semantics. Students asked about precise differences or meaning in code syntax.

Example:

"const int *iptr vs int *const iptr"

A.1.4 Theory Application. Application of abstract theories or formulas to specific problems.

Example:

"What is the probability that at least 1 error is made?"

A.1.5 Process Explanation or Workflow Help. Students asked for step-by-step explanations or workflows to complete problems.

Example:

"Wouldn't it make more sense to write it as... [alternative equation]?"

A.1.6 Interpretation of Data or Output. Questions about making sense of statistical or empirical results.

Example:

"Interpret a z-value of 0.93"

A.1.7 Comparison or Contrast. Prompts asking for distinctions between similar concepts.

Example:

"What's the difference between misinformation and disinformation?"

A.1.8 Real-Life Examples or Analogies. Requests to explain academic concepts through relatable analogies or real-world scenarios.

Example:

"Cultural and technological events significant to the development of video games."

A.1.9 Validation or Evaluation of Understanding. Used to verify understanding or check answers to academic problems.

Example:

"I think I got this right-can you check my logic?"

A.1.10 Clarification of Instructions or Tasks. Questions about assignment requirements or problem interpretations.

Example:

"Can the alternative hypothesis be about lower means instead of higher?"

A.1.11 Medical Information Seeking. Questions related to health symptoms, biology, or medical advice.

Example:

"Can period cramps cause sciatic nerve pain?"

A.1.12 Information Seeking about Cultural or Entertainment Topics. Requests involving pop culture, media, or entertainment.

Example:

"What does the ending of 'The Bear' season 2 mean?"

A.2 Content Generation

A.2.1 Multiple Choice or Fill-in-the-Blank Questions.

"Choose the correct answer to this physics quiz question."

A.2.2 Example Generation.

"Give me an example of how recursion is used in sorting algorithms."

A.2.3 Code Writing.

"Write a Python function to check if a string is a palindrome."

A.2.4 Summarization.

"Summarize this article on stochastic gradient descent."

A.2.5 Explanation.

"Explain the chain rule in multivariable calculus."

A.2.6 Step-by-Step Solutions.

"Solve this integral step by step."

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A.2.7 Editing or Improving Writing.

"Improve the clarity of this paragraph in my essay."

A.2.8 Outline Generation.

"Create an outline for an argumentative essay on climate change."

A.2.9 Definitions and Comparisons.

"Define utilitarianism."

"Compare Locke and Hobbes on political authority."

A.2.10 Academic Citation.

"Format this source in APA 7th edition."

A.2.11 Email or Letter Generation.

"Write a professional email requesting a deadline extension."

A.2.12 Job Application Content.

"Turn this experience into bullet points for a resume."

A.3 Student-Al Interaction

A.3.1 Uncertainty or Confusion Expression.

"I'm not sure if this is correct. Can you double-check?"

A.3.2 Self-Reflection or Learning Awareness.

"I think I understand it better now."

A.3.3 Follow-Up or Clarification Requests.

"Can you explain that last part in simpler terms?"

A.3.4 Interaction Repair or Prompt Revision.

"You didn't follow the last sentence. Let me rephrase."

A.3.5 Appreciation or Gratitude.

"Thanks, that really helped."

A.3.6 Frustration or Dissatisfaction.

"This doesn't help."

A.3.7 Confidence Assessments.

"Okay, I think I got it now."

A.3.8 Humor or Anthropomorphism.

"You're smarter than my professor."

A.3.9 Learning Goal Setting.

"I want to practice derivatives today."

A.4 ChatGPT's Reactions

A.4.1 Apologies.

"I apologize for the mistake in my previous response."

A.4.2 Stated Limitations.

"I'm unable to execute code."

A.4.3 Unintended or Inconsistent Answers.

"I apologize if my previous message was unclear. Let me try again."

A.5 Language Use

A.5.1 Rewording.

"Rephrase this to sound more academic."

A.5.2 Grammar Check.

"Fix the grammar in this paragraph."

A.5.3 Rhetoric.

"Give me examples of rhetorical devices."

A.5.4 Synonyms or Antonyms.

"What's a more formal word for 'get'?"

A.5.5 Translation.

"What's the best way to say this in a formal Chinese email?"

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