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

ANONYMOUS AUTHOR(S)

The widespread adoption of chatbots and large language models has significantly impacted various aspects of daily life. This study employs mixed methods to analyze ChatGPT logs from 36 undergraduate students, providing a comprehensive examination of how this technology is integrated into academic contexts. ChatGPT had diverse applications with the most prevalent uses centering on essay writing assistance. We identify more dynamic scenarios, such as students utilizing ChatGPT to generate and learn computer code across multiple programming languages. The study explores the evolving parasocial relationship between students and ChatGPT, particularly focusing on conversational repair processes and how these interactions change over time. Building upon previous research in human-chatbot interactions, we offer insights into the nuanced ways students engage with AI-powered language models. These findings inform a set of design recommendations aimed at enhancing future chatbot interactions and contributing to the ongoing discourse on the role of AI in education and beyond.

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## 1 Introduction

The rapid proliferation of large language models (LLMs) and chatbots, exemplified by ChatGPT, has fundamentally altered the landscape of information access and task assistance across various domains, including education. As these AI-powered tools become increasingly integrated into academic environments, there is a pressing need to understand how students interact with and utilize these technologies in their daily academic pursuits, prompting discussions on whether we should and how we may integrate LLM-driven chatbots more deeply into educational settings [73]. OpenAI's announcement of ChatGPT Edu on May 30, 2024, a version of ChatGPT claimed to be built for universities to responsibly deploy AI following initial partnerships with several US universities [56], has sparked more cautious optimism and worries on this issue [11]. Despite the growing body of research on AI in education, there remains a significant gap in our understanding of the nuanced, real-world applications of ChatGPT by students, particularly in higher education settings.

This lack of comprehensive insight poses several challenges for educators, policymakers, and technologists alike. While the potential benefits of AI-assisted learning are evident, concerns about academic integrity, the development of critical thinking skills, and the long-term impacts on learning outcomes persist. Moreover, the dynamic nature of student-AI interactions, which can range from simple query-response exchanges to complex, multi-turn conversations, adds layers of complexity to this issue. Traditional approaches to studying technology use in education often rely


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on self-reported data or controlled experiments, which may not capture the full spectrum of spontaneous, authentic interactions that occur between students and AI tools like ChatGPT.

Previous research in this area has primarily focused on isolated aspects of AI use in education, such as its impact on specific subjects or its role in cheating prevention. However, these studies often fail to provide a holistic view of how students integrate AI tools into their broader academic strategies and workflows. Additionally, the rapid evolution of LLMs means that findings from even a few years ago may not fully reflect the current capabilities and uses of these systems.

Our study addresses these gaps by employing a mixed-methods approach to analyze complete ChatGPT usage logs from 36 undergraduate students. This novel methodology provides unprecedented access to authentic, unfiltered interactions between students and AI, offering a comprehensive view of real-world usage patterns. By examining the full spectrum of conversations, from brief queries to extended dialogues, we gain insights into the nuanced ways students integrate ChatGPT into their academic routines.

Our findings reveal diverse applications of ChatGPT in academic contexts, with the most common uses centered around essay writing assistance and accessing school-related information. However, our analysis also uncovers more sophisticated scenarios that extend beyond these primary applications. For instance, we observe students leveraging ChatGPT for coding assistance across various programming languages, demonstrating the tool's versatility in supporting complex, technical tasks.

Moreover, we identify and explore further the parasocial relationship that develops between students and ChatGPT. We examine how this relationship evolves over time, particularly focusing on conversational repair processes—the ways in which students and the AI system navigate misunderstandings or incorrect responses. This aspect of our study provides valuable insights into the cognitive and social dimensions of human-AI interaction in educational contexts.

Our findings build upon and extend previous work in human-chatbot interactions, offering a more nuanced understanding of how AI is integrated into academic life. Based on these insights, we propose design recommendations aimed at enhancing future interactions with chatbots, with potential implications for both educational technology development and pedagogical practices.

## 2 Related Work

We identify two primary domains that anchor our research: the use of LLMs by college students, particularly in educational settings, and the broader field of human-chatbot interaction within the framework of HCI.

### 2.1 LLMs and college students

The possibilities for the use of such AI tools are manifold. ChatGPT has been applied in multiple fields, such as education [28], media [58], marketing [37], finance [19], health care [7], science [71, 75], and more [3].

In this work, we focus on understanding how students use LLM tools like ChatGPT. The application of LLMs in educational settings is a growing area of research, with several studies exploring their potential benefits and challenges [41, 44, 47].

ChatGPT, in particular, has emerged as a significant academic tool for students in higher education, raising important questions about the integration of AI in learning environments [73]. While existing research often prioritizes educators' perspectives in evaluating the potential and pitfalls of ChatGPT, there is a critical need to foreground students' experiences and viewpoints to gain a more comprehensive understanding [68, 70]

Recent studies have begun to explore the various ways students engage with ChatGPT. For instance, researchers have investigated how students use ChatGPT to develop specific academic skills, such as improving their English writing abilities [22, 32]and learning programming [39, 54, 80], highlighting these as common use cases among students. Broader investigations have also been conducted to understand the overall patterns of ChatGPT usage in academic contexts. Von Garrel and Mayer [73] conducted a national survey of students in Germany, identifying twelve distinct academic uses of ChatGPT, including writing assistance, creative thinking, and debugging coursework-related issues.

Similarly, Jishnu et al. [38] surveyed students in higher education and found that content creation and information seeking are primary motivations for using ChatGPT. Their study also revealed discipline-specific variations, suggesting that students' preferences for using ChatGPT differ significantly across academic fields. Interestingly, Jishnu et al. [38] also noted that, beyond academic purposes, students utilize ChatGPT for personal development tasks such as planning and decision-making in daily life, pointing to new avenues for research on non-academic applications of ChatGPT among students.

The reception of ChatGPT in educational contexts has been mixed, characterized by both enthusiasm and skepticism [68] . Proponents argue that ChatGPT can support skill development and enhance learning, advocating for its integration into teaching and learning processes [66]. However, critics have raised concerns about issues related to academic integrity, bias, fairness, and students' over-reliance on AI tools, calling for more stringent governance of ChatGPT's use in education [14].

Based on the above literature, research on how students in higher education use ChatGPT is still emerging, with most studies narrowly focusing on specific educational settings and academic applications. There is a pressing need to expand this understanding to include how students utilize ChatGPT in their daily lives, beyond academic tasks, to encompass personal development and other non-academic uses.

Methodologically, most existing studies on students' use of ChatGPT rely on self-reported surveys [1, 68, 70, 73], which are useful for gathering large-scale data but have inherent limitations in accurately capturing true user behavior. While some studies have analyzed actual interactions between students and ChatGPT, these are often limited to specific contexts or short time frames, such as a single course duration [32, 39]. The absence of detailed, longitudinal data on students' interactions with ChatGPT has restricted a deeper understanding of how these tools function within educational settings.

Furthermore, theoretical engagement within this research area has been limited. While Jishnu et al. [38] employed the Uses and Gratification Theory and Strzelecki [70] drew upon and developed aspects of the Technology Acceptance Theory, much of the existing work focuses on observable behaviors without delving into or extending theoretical frameworks that could inform broader implications, as highlighted by Følstad et al [24]. This gap suggests a need for more nuanced methodological approaches and theoretical explorations that can enrich our understanding of students' interactions with ChatGPT, addressing the broader implications of LLMs in educational and personal contexts.

### 2.2 HCI and Chatbots

Research in Human-Computer Interaction (HCI) has significantly contributed to our understanding of how users perceive, interact with, and respond to chatbots and AI-driven interfaces. As chatbots become more integrated into everyday life, these studies offer valuable insights into the dynamics of human-chatbot interaction, highlighting both opportunities and challenges associated with AI use.

*Overview of human-chatbot interaction.* Chatbots are at the forefront of this shift, transforming how humans engage with computers [8]. Defined as computer programs that communicate with users through natural language [67], chatbots have evolved considerably with the advent of advanced AI models like ChatGPT. ChatGPT, a large language model powered by the GPT (Generative Pre-trained Transformer) architecture, is specifically designed to generate coherent and contextually relevant text-based responses, simulating human-like interactions in a conversational setting [55].

The rise of ChatGPT has redefined the role of AI-driven chatbots, greatly enhancing the quality and frequency of interactions between users and AI. Examining how humans interact with chatbots provides insights into the dynamic influence between technology and its users, reflecting the broader mutual shaping between technology and society [6]. Moreover, chatbots pose significant ethical challenges, including concerns about privacy, data security, and the biases that may be embedded within AI algorithms [62]. By investigating human experiences and interactions with LLM-based chatbots, researchers can better identify ethical risks and contribute to the development of guidelines and regulations that ensure chatbots are integrated into daily life in a secure and beneficial manner.

Previous studies have explored human-chatbot interactions from multiple angles, often focusing on aspects such as user acceptance, trust, and user experience, which involve examining users' internal states and expectations. However, these areas of study are not fully accessible through the interaction data we have collected. Consequently, our focus shifts towards identifying the observable themes and patterns within human-chatbot conversations that have been highlighted in prior research, with a specific emphasis on student-chatbot interactions. This approach allows us to draw directly from the conversational data, offering a grounded understanding of how students engage with AI chatbots in educational and personal contexts.

*Chatbot use by students.* AI-based chatbots to become increasingly prominent in educational environments, reshaping traditional learning paradigms [4, 35, 53, 60, 83]. By simulating human-like interactions, AI chatbots engage students in interactive learning experiences, providing dynamic and immediate responses that can significantly enhance the educational process [20, 33]. These chatbots offer real-time assistance, addressing student queries [17, 18, 40], supporting assignment completion and research efforts [25, 39, 80, 80, 83], and even extending mental health support to students in need [16].

While the advantages of integrating chatbots into educational settings are clear, these benefits come with inherent risks. Security concerns, such as data privacy and unauthorized access to sensitive information, pose significant challenges [35, 60]. Additionally, the potential for chatbots to disseminate misinformation due to their reliance on large-scale, unverified data sources raises questions about the reliability and accuracy of the information provided [71]. Furthermore, the lack of scientific rigor in some chatbot applications can undermine their educational value, necessitating a careful balance between leveraging AI for student support and maintaining standards of academic integrity.

*User-Chatbot Interaction.* Chatbots often fail to meet user expectations, resulting in dissatisfaction and skepticism [8, 36, 45, 81]. Failures can occur when chatbots provide incorrect answers, misunderstand user intent, or respond in ways that seem unnatural or irrelevant. These shortcomings can disrupt the user experience and diminish trust in the technology [45, 81]. From the user's perspective, Li et al. [42] found that users employ various coping strategies when faced with conversational issues, such as rephrasing their input, repeating keywords, or shifting to related topics. However, Zaroukian et al. [82] highlighted an automation bias, where users often accept incorrect chatbot responses due to the overall perceived accuracy of chatbots, which can undermine successful interactions. Users may also contribute to conversational breakdowns by using ambiguous language, making spelling or grammar errors, or engaging in non-sensical or offensive speech, all of which can impair chatbot performance [34, 57].

From the chatbot's perspective, Chaves and Gerosa [10] propose the concept of conversational and social intelligence to address these challenges. By enhancing these aspects, chatbots can better manage conversational issues and improve interactions with users, fostering more effective communication and reducing misunderstandings.

*Emotions generated during human-chatbot interaction.* Researchers emphasize the importance of examining the various emotions generated during human-chatbot interactions, as these emotions play a critical role in shaping the overall user experience. Negative emotions, such as frustration or confusion, are often the primary reasons users discontinue conversations, while positive emotions can help prevent communication breakdowns and enhance the effectiveness of chatbot interventions [72, 76]. Moreover, chatbots that display emotional cues, such as expressing empathy or adjusting their responses based on perceived user mood, can significantly increase users' willingness to continue interactions, making the chatbot appear more supportive and engaging [23, 43, 59] Additionally, some studies focus on chatbots' ability to regulate user emotions. Chatbots can influence users' emotional states over time by asking about their mood, offering behavioral and cognitive interventions, and recognizing stressful situations to suggest appropriate emotional regulation strategies [16, 29, 49, 50]. These capabilities not only enhance the user experience but also position chatbots as potential tools for emotional support, extending their utility beyond simple informational exchanges.

*Parasocial Relationships in human-chatbot interaction.* Chatbots, through their use of natural language and conversational formats, simulate human-like interactions, often creating a parasocial dynamic where users develop one-sided emotional connections despite knowing the chatbot is not human [46, 74]. This phenomenon reflects how chatbots can mimic interpersonal communication, allowing users to engage with them as they would with another person.

Research has explored the anthropomorphism of chatbots, examining how their perceived humanness influences interactions. Factors contributing to this perception include linguistic attributes like grammar, plausibility, and language style [15, 79], as well as psychological and interactional qualities such as humor, interactivity, and perceived consciousness [5, 77]. Emotional characteristics like empathy and self-disclosure further enhance chatbots' human-like qualities, impacting user engagement and satisfaction. However, Crolic et al. [13] found that anthropomorphism can have mixed effects: it negatively impacts users who are angry, possibly due to unmet expectations of chatbot efficacy, while having neutral effects on users in a calmer state. Additionally, Monteayor, Halpern, and Fairweather discussed the current fundamental limits of simulated empathy from AI in the field of clinical medicine and care, questioning the application of AI in health care and mental support [52].

The absence of genuine empathy and emotional intelligence in chatbots can lead to user frustration, especially in contexts where emotional support is critical, such as during discussions of personal or academic stress (Fryer et al., 2019). This highlights the limitations of chatbots in fully replicating the nuanced emotional dynamics of human-to-human interactions.

Overall, our study diverges from prior research by focusing specifically on the detailed, long-term interactions between students and ChatGPT, analyzing both academic and personal use cases. Unlike many existing studies that rely on self-reported surveys or short-term observations, we employ a mixed-methods approach that includes direct analysis of interaction logs, providing a richer, more nuanced understanding of how students engage with chatbots over time. This approach allows us to explore the unique dynamics of student-chatbot relationships, including the emergence of parasocial interactions and the practical challenges students face, offering new insights into the role of chatbots in educational and personal contexts.

## 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. 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.

Though the chat logs themselves do not explicitly contain links to personal information such as email addresses, 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.

Some details of the data are shown in Table 1. Our dataset spans over a year of activity, 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 |

## 4 Methods

Our analysis employs mixed methods to thoroughly capture both the qualitative and quantitative aspects of the data. Initially, we engage in qualitative coding on a selected small sample of the dataset to discern coherent categories within the student prompts. This step is critical for establishing a solid foundation for subsequent analyses and is detailed in Section 4.1. Following the establishment of these categories, we leverage the insights gained to construct classifiers. These classifiers are then applied across the entire dataset, allowing us to identify the prevalence of the categories detected in the qualitative coding in the entire dataset (Section 4.2). Finally, to reinforce the validity of our manual coding and automated classification, we additionally employ BERTopic – an advanced topic modeling technique based on BERT – on the entire dataset (Section 4.3).

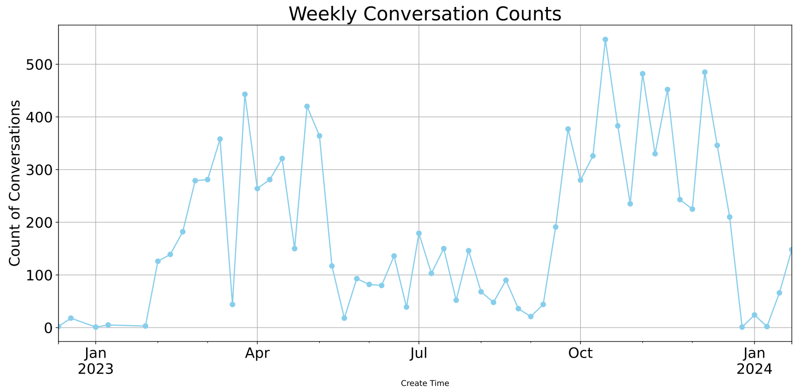


Fig. 1. Timeseries of the conversations in our dataset

### 4.1 Qualitative Coding

We began our analysis with a qualitative examination of the collected data. Using inductive coding, we analyzed both the user text and ChatGPT-generated responses. This process allowed us to condense raw data into categories and themes through valid inference and interpretation [84]. One of the authors conducted the coding using NVivo, a qualitative data analysis software.

Our units of analysis were individual themes in each student's historical conversations with ChatGPT [84]. While the data was formatted in tables, with conversations separated into student entries and ChatGPT responses, we didn't limit our analysis to these physical linguistic units. We recognized that a single code or theme could appear across different conversations, such as students' changing attitudes toward ChatGPT over time.

Our analysis, informed by grounded theory [26], consisted of two stages. The first stage, open coding, aimed to identify general categories related to students' various uses of ChatGPT and the interactions between students and the AI. The second stage, axial coding, involved comparing open codes and their relationships to organize the data into meaningful categories.

Given the extensive nature of our dataset, which included students' conversations with ChatGPT spanning over a year, a comprehensive qualitative coding of all log data was not feasible. We initiated our coding process with the complete historical data from the first twelve students recruited during the initial round of data collection. This involved hand-coding 1,882 user text and ChatGPT responses, providing a foundation for our codebook development.

To expand our analysis and achieve thematic saturation, we conducted two rounds of purposive sampling from the remaining 24 students' log data [31] [12]. In the first round, we randomly selected and coded 10 conversations from each student's historical data. This process led to the identification of a high-frequency category, prompting a second, more targeted sampling round. The second sampling round focused on conversation length and the frequency of title changes within one week. We selected up to 20 conversations per quartile based on these criteria, ensuring a representative sample of diverse interaction patterns. All sampled conversations were then coded using our established scheme. Notably, this second round did not yield any new emerging codes, suggesting approaching saturation.

To ensure we had indeed reached thematic saturation, we conducted a final review of the uncoded data [31]. This multi-stage approach allowed us to develop a comprehensive codebook while efficiently managing the large-scale dataset, providing a robust foundation for our subsequent analyses of student-ChatGPT interactions.

The coding process was iterative and collaborative. Two authors began by conducting two stages of coding on the complete historical data from the first twelve students. This initial coding resulted in a preliminary codebook that included different levels of codes, rationales for code names and relationships, example text from the original data, and additional notes. The coders provided detailed explanations for each code name and included illustrative examples. After this initial phase, the coders compared their codebooks to identify major differences and reach initial agreement. They then proceeded to code the data sampled in subsequent rounds, further refining the initial codebook. Regular meetings were held to discuss and resolve any disagreements, ultimately leading to a consolidated and final codebook. In line with current qualitative research practices, we prioritized reaching consensus between coders rather than calculating inter-rater reliability scores [48].

Our coding process ultimately yielded five primary categories that encapsulate the key aspects of student-ChatGPT interactions: Content Generation (GA), Information Seeking (IC), Language Use (LU), Student Interaction with ChatGPT (SC), and, ChatGPT's Response (CR). The first three categories – Content Generation, Information Seeking, and Language Use – provide insight into the primary ways students utilize ChatGPT in their daily academic activities. The last two categories – Student Interaction with ChatGPT and ChatGPT's Response – offer a more nuanced perspective on the dynamics of the student-AI relationship. Our complete categorization was on multiple levels (described in the Appendix), where we expand on the sub-codes under the five main categories to illustrate how students use ChatGPT in their everyday lives and interact with it. We provide a short description of the top level categories below.

(1) **Information Seeking**: This category is centered on the retrieval of factual information, clarification of concepts, or answering specific questions. The primary goal here is knowledge acquisition and understanding. It makes up around 41% of the content we coded. Within this category, we have sub-codes that reflect students' everyday information needs [65] when student use ChatGPT for information seeking, such as academic content job application, medical issues, social and cultural issues, and so on.
(2) **Content Generation**: This category focuses on the creation of original or creative content, such as stories, essays, poems, scripts, code, or other written forms. It makes up around 30% of the messages we coded. In this context, students provide prompts, and ChatGPT generates new text based on these inputs, emphasizing creativity, originality, and stylistic elements. Within this category, we have identified several sub-codes representing content generation across different topics, such as academic content generation in different subjects, job application content generation, brainstorming of ideas besides academic and job application content, and so on.
(3) **Student ChatGPT Interaction**: This category focuses on the human aspect of the student-ChatGPT interaction, particularly how students respond to ChatGPT's answers and communicate with the AI in specific ways. It makes up 15% of the messages we coded. Under this category, we identified the sub-codes such as asking following up questions or commands, pushing back ChatGPT's answers, emotional expressions towards ChatGPT, parasocial relationships between student and ChatGPT, and so on.
(4) **Language Use**: This category (making up 7% of the messages) involves the manipulation of language in various forms, including sub-codes on paraphrasing, finding synonyms or antonyms, adjusting rhetorical style, translating text, and performing grammar checks. In this category, students provide text, and ChatGPT executes specific language tasks.
(5) **ChatGPT's Reaction**: 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

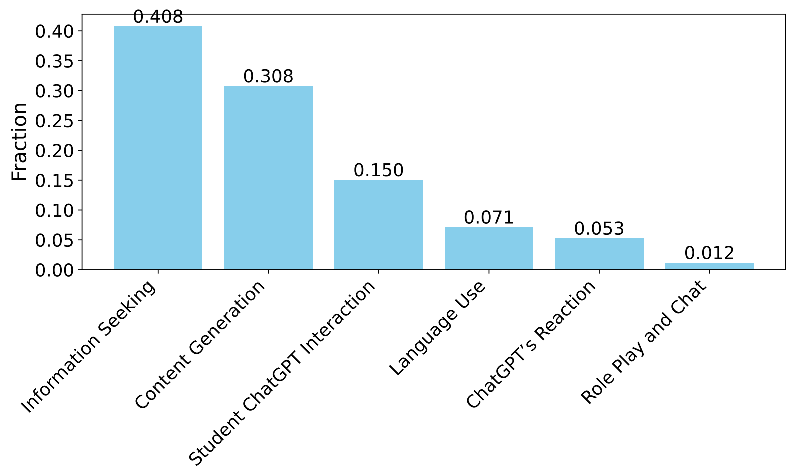


Fig. 2. Command categories and their prevalence after qualitative analysis

student prompt, . Special attention is given to instances where conversational issues arise – those interactions that may be problematic or unsatisfying for the user [61].

(6) **Role Play and Chat**: This category emphasizes students' use of ChatGPT for role-play and conversational simulations, where they engage the ChatGPT as a fictional character in scenarios that mimic real-life social interactions or hypothetical conversations. We found only 1% of our samples belong in this category, corresponding to one student in our sample, so we did not assign a sub-code under this category.

The prevalence of these categories is shown in Figure 2.

### 4.2 Automated Classification of Categories

Using the categories identified from the initial qualitative coding as a foundation, we proceeded to develop a classifier to analyze the larger dataset derived from the 24 users in the second phase of data collection. To construct this classifier, we employed word n-grams within the range of (1,3) as features, aiming for a nuanced capture of linguistic patterns across the user prompts. Given the variability in the dataset with twelve different classes, the distribution of samples across these classes was not uniform, introducing a notable class imbalance. To address the imbalance, we applied the ADASYN algorithm [27] to oversample the minority classes, thereby enhancing the representativeness of each category within the model training process.

The process of transforming user prompts into n-grams (1, 3) facilitated a multi-class classification approach. To optimize the classifier's performance, we utilized GridSearchCV[1] to determine the best set of hyperparameters for the logistic regression model. The optimal configuration included L2 regularization and the lbfgs solver, with an adjustment for the class imbalance through the implementation of balanced class weights. We trained the classifier for all categories and subcategories where the accuracy was satisfactory (over 85%) to apply to the full dataset. The results of this classifier's performance, including accuracy and class-specific metrics for the top level categories is summarized in Table 2. The full results for all the subcategories is shown in the Appendix.

[1]https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

Table 2. Predicted category, prediction model metrics.

| Category | Accuracy | Precision | Recall | F1 | AUC ROC |
|---|---|---|---|---|---|
| Content Generation | 0.903 | 0.920 | 0.956 | 0.938 | 0.843 |
| Information Seeking | 0.916 | 0.928 | 0.976 | 0.951 | 0.785 |
| Students' Interaction with ChatGPT | 0.910 | 0.950 | 0.872 | 0.909 | 0.911 |
| ChatGPT's Response | 0.821 | 0.205 | 0.708 | 0.318 | 0.768 |

### 4.3 Qualitative Analysis for BERTopic

Our final line of analysis applies BERTopic [30] to the user prompts to try to obtain the categories from the data automatically. This step serves both as a validation for our qualitative coding as well as provide automated analysis tools which can help extend our analysis beyond our dataset. We used the Bidirectional Encoder Representations from Transformers (BERT) for contextualized topic modeling. BERT embeddings model the semantic context [51] of words by mapping corpus terms in semantic space "in which distance represents semantic association." [2] We used the BERTopic package [30] to cluster BERT embeddings [63] using Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) [9]. Similar documents in the corpus will be closer to each other. Each document will also be closer to words semantically closer to it.

To find the optimum number of topics for the BERTopic model, we trained 25 different models by changing minimum cluster size (an HDBSCAN hyperparameter) by increments of 10 at a time.[2] The first model's minimum cluster size was set to 15, and the last model was set to 255. The higher the minimum cluster size, the lower the number of clusters - and the lower the number of identified topics. To identify the top model, we calculated the coherence score of each model using the Gensim *CoherenceModel* feature.[3] Coherence values have been found to be good at approximating human ratings of a topic model "understandability" [64]. We selected the model with the top coherence score (0.39), with a minimum cluster size of 50, that produces a topic model with 88 topics.

After the topics were identified using BERTopic package, we qualitatively analyzed each of the topics. We randomly sampled 10 user text and 10 ChatGPT text under each topic for qualitative analysis. Two of our researchers read through all the samples under each topic, summarized the topic of the samples and wrote a description for each topic. Our two researchers made detailed notes, providing reasons for each topic name and highlighting topics that may not be substantive for our analysis. They met and compared their understanding of the samples under each BERTopic to determine if there were any major differences and disagreement. This process allowed us to organize the topics into twelve themes. Using the BERTopic library, we merged all topics within each theme.[4]

The twelve themes identified were: (1) Science, Technology and Management: engagements focused on questions about science, technology, and management. Most of these discussions are about schoolwork; (2) Coding: students are either asking for code generation or engaging in rewriting code, again mostly for school assignments; (3) Social Science and humanities: mostly about schoolwork (e.g., asking about historical events or social science theory); (4) Math: questions about mathematical and statistical concepts (e.g., p-value, kurtosis); (5) Computer Science: discussing computer science concepts (e.g., operating systems); (6) Internship: preparing for an internship by working on the CV and a design assignment for the job interview; (7) Music: asking about music concepts (e.g., pitch); (8) Synonym: finding synonyms for words; (9) email: asking ChatGPT for assistance in writing emails, especially important and formal emails;

[2]https://hdbscan.readthedocs.io/en/latest/parameter_selection.html?highlight=min_cluster_size#selecting-min-cluster-size
[3]https://radimrehurek.com/gensim/models/coherencemodel.html
[4]When"topics are merged, then a weighted average of topic embeddings is taken based on the initial topic sizes." Source: https://maartengr.github.io/BERTopic/api/bertopic.html#bertopic._bertopic.BERTopic

(10) Polite interactions: using words like thank you, sorry etc.; (11) Financial: asking about financial concepts and recommendations; and (12) Citation: producing citations for generated materials or searching for information sources.

## 5 Findings

Below, based on the findings form both qualitative and computational analysis, we present the findings of our study in three main sections. The first section (Section 5.1) provides an overview of the total prevalence of various categories we identified in the data, the second section (Section 5.2) provides a descriptive analysis of how some students use ChatGPT in various contexts, including a detailed examination of its use concerning sensitive topics. In the final section (Section 5.3), we explore some special patterns and themes in student-ChatGPT interactions, highlighting both effective and potentially problematic interaction.

### 5.1 Overall Prevalence of Various Categories

Table 3. Total categories from qualitative analysis (Q) and BERTopic topic modeling (B). Only categories making up at least 5% of the content are shown below. The full table with all categories can be found in the Appendix.

| Category | # | Frac. | Source |
|---|---|---|---|
| Information Seeking | 9,010 | 0.855 | Q |
| Content Generation | 8,213 | 0.780 | Q |
| Student ChatGPT Interaction | 5,217 | 0.495 | Q |
| Science, Technology and Management | 3,005 | 0.285 | B |
| Coding | 2,608 | 0.248 | B |
| Social Science and Humanities | 2,514 | 0.239 | B |
| Math | 1,241 | 0.118 | B |
| Content Generation → multiple choices and filling in blanks questions | 1,188 | 0.113 | Q |
| Computer Science | 512 | 0.05 | B |

Table 3 shows the result from applying the classifier developed in Section 4.2 on the entire dataset, and BERTopic (Section 4.3). The table shows both the total count of messages in each category as well as the fraction. From Table 3, first, we observe that the categories from extending the qualitative coding using the classifiers (Q) and BERTopic (B) are almost orthogonal indicating the value of our mixed methods approach. The most common uses of ChatGPT for students is in information seeking, and content generation making up almost 80% of the messages. Students clearly use ChatGPT for school related tasks, as evident from the prevalence of BERTopic categories like Coding, Match, Social Sciences, etc. Around 11.3% of the requests involve students directly copy pasting (possibly) assignment questions into ChatGPT. In the next section, we provide a qualitative deep dive into uses of ChatGPT by students for various daily tasks.

### 5.2 Students' Daily Use of ChatGPT

As discussed in Section 4.1, we divided students' daily uses of ChatGPT into four main categories: Information Seeking, Content Generation, Language Use, and Role-play & Chat. In this section, we describe these categories and subcategories in detail.

#### 5.2.1 Information Seeking.

Our analysis revealed that students utilize ChatGPT for diverse information-seeking purposes, which we categorized into six sub-themes: academic content, job application-related content, personal topics, social and cultural issues, health and medical information, and information about ChatGPT itself.

*Information seeking for academic content.* Students employ ChatGPT across various academic disciplines, particularly in STEM fields. They seek precise definitions, concepts, and relevant theories, as well as clarification of complex concepts or research methodologies. Additionally, students use ChatGPT to evaluate social impacts and consequences within specific contexts. This usage pattern indicates that students rely on ChatGPT not only for factual information but also to facilitate critical thinking on more complex topics.

*Information seeking for job application-related content.* Students primarily seek guidance on resume writing advice, such as content inclusion, behavioral questions like post-interview follow-ups and salary negotiations, and cover letter composition. Some students attempted to use ChatGPT for gathering current job listings, but its performance was unsatisfactory due to the lack of real-time internet connectivity in the version used.

*Information seeking for personal topics.* Students' use of ChatGPT extends beyond academic matters to personal interests, including lifestyle-related queries such as meal planning and vacation planning. Some students asked investment-related questions, which ChatGPT cannot answer due to OpenAI policy. Notably, some instances of potentially malicious use were identified, such as seeking private information or tax avoidance strategies, raising privacy and ethical concerns.

*Information seeking on social and cultural issues.* Students explored various topics, including legal frameworks and social movements of specific historical periods, historical perspectives on current political and military debates, and geographic disputes, religious customs, and cultural practices.

*Information on health and medical information.* Students sought information on disease treatments, health-related guidance, and medical history, such as the geological origin of COVID-19.

*Information seeking regarding ChatGPT.* Students queried ChatGPT about its own capabilities, limitations, and best practices for effective use in academic and personal contexts. This behavior demonstrates students' AI literacy and desire to optimize their interactions with the tool. It also highlights the importance of critical thinking when relying on AI for self-description and the need for cross-checking information from multiple sources. This information-seeking behavior regarding ChatGPT itself emphasizes the dynamic relationship between users and AI tools, underscoring the importance of developing critical evaluation skills in the context of AI-assisted learning and information retrieval.

#### 5.2.2 Content Generation.

Our analysis revealed five sub-themes within the content generation category: (1) academic content generation, (2) job application-related content generation, (3) email or notice letter generation, (4) generation of content on personal topics, and (5) brainstorming of ideas beyond academic and job applications.

*Academic content generation.* Academic content generation emerged as the most prevalent category, comprising four main types: answering multiple-choice, true/false, and fill-in-the-blank questions; generating academic essays; code generation; and citation generation. These applications span various disciplines, including humanities, social sciences, natural sciences, computer science, engineering, and the arts.

Students predominantly used ChatGPT to generate answers for multiple-choice, true/false, and fill-in-the-blank questions in large quantities. Most students relied heavily on ChatGPT's output without additional verification or further dialogue. Only a few engaged in follow-up discussions or verification of the provided information.

For academic essay generation, most students directly provided assignment prompts, including directions and rubrics, to ChatGPT. Some employed a more nuanced approach, posing questions from various angles before requesting essay generation. These students often asked ChatGPT to paraphrase generated paragraphs to enhance originality. Additionally, some students used ChatGPT to generate discussion posts for their courses, sometimes based on other students' posts.

Programming code generation was another frequent use, with students requesting code in languages such as R, Python, Java, and C++. While most provided complete task instructions, some students asked ChatGPT to achieve goals using alternative methods or to replace parts of existing code. Citation generation was observed in several cases, with students requesting APA or Chicago format citations based on paper links, titles, or DOIs. However, ChatGPT's performance in this area was often limited due to internet access restrictions.

*Job application content generation.* Many students utilized ChatGPT for job-related content, including generating answers to interview questions, creating resumes, and composing cover letters. Students often requested "sophisticated yet personalized" content that portrayed them as "professional." Some students provided paragraphs of previous experiences and asked ChatGPT to convert them into bullet points or to generate different versions of resumes tailored to specific job positions.

*Email and letter generation.* Email and letter generation primarily focused on administrative content. These often involved complex or uncommon situations requiring careful attention to tone and wording. Examples included requests for financial aid from university departments or appeals for additional exam opportunities.

*Brainstorming of ideas.* Students employed ChatGPT for brainstorming beyond academic and job-related contexts. This included generating jokes on specific topics, ideas for social media content (e.g., blog topics, captions), and activity plans (e.g., birthday parties, book talks, travel plans, product promotions).

*Other personal topics.* The study identified various unique cases of personal content generation. Due to the small sample size and lack of suitable meaningful categories, these cases were grouped together without further detailed discussion.

*5.2.3 Language Use.* Our analysis revealed that students frequently utilize ChatGPT for various language-related tasks. We identified five primary categories of language use: grammar check, rewording, rhetoric, synonyms or antonyms, and translation.

*Grammar Check.* Students often employ ChatGPT as a grammar checking tool, leveraging its natural language processing capabilities to identify and correct grammatical errors. This usage extends beyond simple proofreading, as students frequently ask ChatGPT to explain the grammatical rules underlying the corrections. For instance, students might submit entire paragraphs or essays for review, seeking not only corrections but also explanations of complex grammatical structures such as conditional clauses or proper use of gerunds and infinitives.

*Rewording.* Rewording emerged as a significant use case, with students requesting ChatGPT to rephrase sentences, paragraphs, or entire documents. This application serves multiple purposes, including improving clarity, adjusting tone, and avoiding plagiarism. Students often provide specific instructions for rewording, such as simplifying complex text, adopting a more formal or informal tone, or maintaining the original meaning while completely changing the sentence structure.

*Rhetoric.* Students turn to ChatGPT for assistance with rhetorical devices and strategies, demonstrating an interest in enhancing the persuasiveness and impact of their writing. Requests in this category include generating examples of specific rhetorical devices (e.g., metaphors, analogies, or parallelism), analyzing the rhetorical structure of given texts, and advice on constructing arguments for debates or persuasive essays.

*Synonyms or Antonyms.* The use of ChatGPT for finding synonyms and antonyms is widespread among students, indicating a desire to expand their vocabulary and enhance the variety of their language use. Students often request synonyms for common words to avoid repetition in their writing, or seek more sophisticated alternatives to elevate the tone of their text.

*Translation.* ChatGPT's translation capabilities are frequently utilized by students for various purposes. Beyond simple word-for-word translation, students often seek cultural context and idiomatic expressions in the target language. They may ask for translations of colloquialisms or request explanations of how certain phrases might be interpreted in different cultural contexts. Some students use ChatGPT to compare translations from multiple sources, asking the AI to explain discrepancies or nuances between different versions.

*5.2.4 Role Play and Chat.* Our qualitative analysis revealed an emerging trend of students using ChatGPT for role play and conversational simulations. This usage pattern demonstrates students' exploration of AI's capabilities beyond academic and professional applications, venturing into social and emotional domains.

One notable case involved a student engaging with ChatGPT as a friend, expressing a desire for social interaction. Despite initial hesitation, the student quickly immersed themselves in conversation, discussing topics such as music and television series, and soliciting ChatGPT's opinions. This behavior suggests a potential use of AI as a social surrogate, particularly for individuals experiencing feelings of isolation or loneliness. The student's initial message (paraphrased) exemplifies this sentiment:

> This feels a bit unusual, I must admit. However, I really want to talk with someone. Might you be open to a chat like a friend with me?

Throughout the conversation, the student conveyed a sense of loneliness and a desire for casual dialogue. This interaction highlights the potential for AI to serve as a conversational partner, albeit with significant limitations. However, this case also illustrated the current constraints of AI in fulfilling complex social roles. The student often used declarative sentences without clear requests or questions, which led to ChatGPT repeatedly asking for specific instructions based on its function. This interaction pattern resulted in the student expressing frustration and questioning ChatGPT's ability to understand them.

### 5.3 Human-LLM interaction

In this section, we examine the patterns of interaction that emerge from students' conversations with ChatGPT. We identify three distinct types of interactions: (i) students adapting their interaction patterns based on the topic of discussion, (ii) students' responses to ChatGPT's failures, and (iii) parasocial interactions and anthropomorphism in student-ChatGPT engagements.

*5.3.1 Interaction Patterns Based on Topic and Questioning Style.* Our data reveal that students' interaction patterns with ChatGPT vary depending on the topic of discussion and the individual's approach to questioning. This variability is primarily reflected in the style of questioning and the length of conversations, especially when follow-up questions are involved.

For topics such as coding and mathematical problem-solving, students tend to engage in longer, more detailed interactions. These conversations often include multiple exchanges, where students ask follow-up questions or request 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 allows students to refine their understanding and receive targeted guidance through problem-solving steps tailored to their specific needs.

Conversely, for open-ended questions, such as those related to social sciences or cultural topics, interactions are typically more succinct. These conversations usually consist of a single query and a direct response, with students seeking generalized information or conceptual explanations rather than engaging in extended discussions. This pattern suggests that students might perceive these topics as requiring less detailed exploration or iterative feedback compared to technical subjects.

When questions are factual or descriptive with a clear, definitive answer, the interactions tend to be brief. Examples include queries like, "Which insect is considered aquatic collector feeders?" or "Which renowned composer is Brahms paying tribute to in his Symphony No. 1, evidenced by the use of a recognizable motif and the tonal progression from C minor to C major?" In these cases, the straightforward nature of the questions and the expectation of a specific answer limit the depth and duration of the conversation.

Students' questioning approaches also vary significantly. Some students ask fully detailed questions, clearly articulating the context and the specific information they need, which often results in more precise and relevant responses from ChatGPT. Others, however, use minimal keywords or phrases, relying on ChatGPT to infer their intent, which necessitates a higher degree of interpretive flexibility from the AI. Another notable pattern is students repeating the same questions to ChatGPT, seemingly to explore different responses.

#### *5.3.2 Students' Interaction with ChatGPT After Failures, Bias, or Mistakes.*

*ChatGPT's Responses.* ChatGPT's responses to students often reveal its limitations and boundaries in handling specific requests. Common issues include: (a) explicitly stating its inability to address certain topics due to neutrality requirements, such as not holding personal beliefs; (b) outdated knowledge, given that its information base is not continuously updated; (c) execution issues, such as its inability to run code directly; (d) access limitations to external databases or personal files; (e) insufficient input from students, leading to incomplete responses; (f) legal constraints; and (g) restrictions on providing financial or investment advice.

Sometimes, even when ChatGPT provides an answer, it clarifies its limitations, acknowledging potential gaps in its abilities. However, ChatGPT also encounters notable failures, such as providing different answers to the same question when asked repeatedly by a student, causing confusion. Other failures include not understanding the question, misinterpreting prompts, or generating fabricated information that appears plausible but is false. Additionally, ChatGPT occasionally produces unintended or biased responses. For instance, when asked about a book's discussion on racism, ChatGPT denied any such content despite its presence. In another case, ChatGPT responded defensively when questioned about the reusability of code it provided, insisting it should generally be reusable, even when it was not.

ChatGPT often attempts to mitigate misunderstandings by apologizing for errors or inaccuracies, but these responses highlight the AI's limitations in fully addressing the nuances of human requests and expectations.

*Students' Reactions and Coping Strategies.* Students employ various strategies to cope with ChatGPT's failures or errors. Commonly, they revise their initial questions to simplify them, making them easier for ChatGPT to understand, particularly when ChatGPT fails to grasp or misinterprets the original prompt. In some cases, students ask ChatGPT to refine its previous answers by providing more detailed instructions or additional context.

Students frequently challenge ChatGPT's incorrect responses, particularly in programming and mathematical proof contexts, where precision is critical. They often push back against ChatGPT's mistakes, pointing out specific errors and demanding corrections. When ChatGPT generates false or misleading information, some students even attempt to correct or educate the chatbot, engaging in an unusual reversal of roles where the user teaches the AI.

We also observed an evolution in students' coping strategies. Initially, students tended to overwhelm ChatGPT with overly detailed prompts, leading to misunderstandings. Over time, they adapted by breaking down information into smaller, manageable sections, prefacing their input with clarifications like, "I am going to teach you a ... topic, it is long so I will send it to you section by section." This shift demonstrates a growing sophistication in how students manage their interactions with ChatGPT, reflecting their ability to adapt their communication style to the AI's constraints.

#### 5.3.3 Parasocial Student-ChatGPT Interaction and Anthropomorphism.

*Human-like Conversation with ChatGPT.* Our analysis shows that students often engage with ChatGPT in a human-like manner, using polite and socially coded language. Common behaviors include exchanging greetings like "Hi!" or "Hello!" and expressing gratitude with phrases such as "Thanks!" Additionally, students frequently use modal verbs like "would," "could," and "should," reflecting a polite, conversational style.

Many students, whether consciously or unconsciously, provided human-like feedback to ChatGPT, expressing appreciation or positive reinforcement during interactions. Examples include responses like "Right!", "Cool!", "Yeah," or the use of emoticons and emojis (e.g., " "), often followed by a subsequent question. In other instances, students displayed more casual or emotional reactions, such as starting with "Are you kidding?" or sharing personal feelings like "I feel crazy right now," "I am super unhappy," or "I am feeling weak."

We also observed instances of role-playing and casual conversations, suggesting a parasocial relationship between students and ChatGPT. When students perceived a lack of mutual understanding from ChatGPT, they expressed feelings of resentment and disappointment. This interaction pattern indicates potential false expectations, where students view the AI's discrete outputs as part of a continuous, shared communicative context, leading to emotional engagement and misplaced anticipation of mutual understanding from the AI.

*Students' Changing Attitudes Towards ChatGPT.* In the early stages of interacting with ChatGPT, students often used polite and socially coded language, including modal verbs like "could," "would," and frequent expressions of gratitude, reflecting a desire to communicate respectfully beyond what was necessary for ChatGPT's comprehension.

While most students maintained a consistent tone throughout their interactions, we observed that one student's attitude shifted noticeably after about a week of frequent use. Initially polite and formal, the student's communication style became more direct and devoid of social pleasantries, marked by an icy tone and straightforward commands. This change suggests an evolving comfort level with the AI, as students adjust their communication to prioritize efficiency over social norms, reflecting a shift from human-like engagement to a more utilitarian interaction.

## 6 Discussion

The introduction of ChatGPT has rapidly transformed the landscape of universities, sparking intense debate among academics about its role in education [68]. While some educators have cautiously embraced this AI-driven tool as a valuable aid [66], others have viewed it with skepticism, fearing its potential misuse [14]. Our findings reveal that students have unequivocally embraced ChatGPT, not just as a convenient academic toolkit but as resource for multiple perspectives in their everyday life. This paper provides detailed insights into how students engage with ChatGPT, offering a grounded perspective on its impact within students' everyday life.

### 6.1 Students' everyday use of ChatGPT

Our findings have implications about the daily use of ChatGPT by students. Below, we problematize the academic use of ChatGPT and then we discuss how it is being used outside of academia.

*6.1.1 Students' nuanced academic use of ChatGPT.* Aligning with previous studies [38], our findings shows that students predominantly use ChatGPT for educational purposes, including information seeking and content generation of academic content across various subjects, and language ability improvement, demonstrating that students are not merely experimenting with the tool but actively integrating it into their learning processes.

Though many previous work have discussed ChatGPT's negative impacts on academic integrity [47] [44] [42] [14], our findings articulated that the nuances in students' ChatGPT use extend beyond simple academic integrity violations, calling for more contexualized examination of students' ChatGPT use for educational purposes. While cheating, such as copying assignments verbatim, is certainly present, it represents only a fraction of the broader landscape of interaction that includes seeking explanations, clarifications, engaging in creative problem-solving on different academic topics, and even including challenging ChatGPT's answers. This reveals that the use of ChatGPT is not just about circumventing academic rules but also about filling gaps in knowledge and supporting personal development. This highlights the complex role ChatGPT plays in education, where it can simultaneously be a tool for learning and a means of academic misconduct.

*6.1.2 Beyond Academic Use: ChatGPT Use in Other Student Everyday Settings.* One of the key insights from our study is that traditional survey-based studies may underestimate the scope of ChatGPT's use [3, 38] because they often fail to capture the nuanced, day-to-day ways in which students engage with this technology. By analyzing real interaction logs, our work provides a richer, more contextualized understanding of students' use of ChatGPT. Our findings articulate different aspects for students' personal development, including job application, guidance on healthier life style, travel plan, after-school activity plan, and even on investment guidance (though ChatGPT is set not to answer this type of question), which reflects the diverse range of support students seek in their everyday lives, illustrating their need for assistance across multiple areas of personal growth.

*6.1.3 Conversational Issues and Coping Strategies.* Adding to previous discussion on LLM Denials of User Requests [78], our findings also show that ChatGPT cannot function on many issues, whether due to regulation policies or its technical inabilities, leading to conversational issues [61]. Our findings focus on the educational settings. Our findings captured students' diverse coping strategies when conversational issues happen between student and ChatGPT. Adding to Li et al. [42]'s findings on user coping strategies in response to conversational issues, such as rephrasing, repeating the same words, or asking a new topic on the same subject, this study finds that many students ask ChatGPT to improve previous answer itself. It is also wroth notice that, though the above-mentioned automation bias [82] is identified in the data, students' trying to push back or correct ChatGPT's answers is also discovered, indicating more user agency in student-ChatGPT interaction.

Meanwhile, several conversational issues arose when students attempted to misuse ChatGPT for malicious purposes. Some students asked ChatGPT to assist with illegal things, such as seeking private information about others or looking for strategies to evade taxes on part-time jobs. After ChatGPT refused these requests, some students became upset or questioned its responses. These instances highlight challenges related to students' use of ChatGPT, particularly regarding privacy concerns and ethical boundaries, emphasizing the need for responsible AI usage in educational settings.

*6.1.4 Students' parasocial relationships with ChatGPT.* ChatGPT does have personification and social intelligence [10] that promotes human-like conversation and parasocial relationships [46], but are not enough for fulfilling students' deep human needs [69] , such as making friends with ChatGPT and mutual understanding. One student implied the feeling of loneliness, not getting used to socialize people at campus, and the willing to talk with someone immediately. However, that student ended up realizing that ChatGPT cannot really understand the student. Tough previous studies have investigated student use of mental health chatbots to address students' stress [16] [21], no previous study reflect this type of use on ChatGPT. Since ChatGPT is not designer as a special mental health chatbot, it remains examination on ChatGPT's function on this use and the necessary intervention mechanisms.

### 6.2 Policy and Design implications

For HCI researchers, these findings underscore the importance of designing AI-driven educational tools that align with students' needs while mitigating the risks associated with misuse [4] [35] [83]. ChatGPT's ability to simulate human-like conversation and provide personalized feedback resonates strongly with students, suggesting that future AI design should prioritize adaptability and responsiveness to user input [46]. Our study also reveals the emotional and parasocial dynamics that can develop between students and AI, pointing to a need for more sophisticated design strategies that account for user expectations, emotional engagement, and the risks of anthropomorphism.

Furthermore, the findings carry significant implications for the CHI community, as they highlight the need for HCI researchers to rethink the design and deployment of AI tools in educational settings. Our work suggests that simply banning or limiting the use of AI like ChatGPT is unlikely to be effective. Instead, there is a critical need to develop AI systems that are transparent, ethically sound, and capable of guiding students towards responsible use. This includes incorporating features that can help identify and correct misuse while still supporting legitimate learning activities.

Moreover, the repeated evidence that students use ChatGPT almost exclusively for academic purposes—and at times, for directly completing assignments—raises important ethical and pedagogical questions. It calls for educational institutions to proactively address these challenges by establishing clear guidelines on the responsible use of AI. This should include strategies for integrating AI literacy into the curriculum, equipping students with the skills to critically evaluate AI-generated content and use it to enhance their learning responsibly.

Concretely, we call upon the CHI community to help design the next generation of AI tooling particularly targeted towards two stakeholders: (i) Educational institutions, and, (ii) LLM providers.

Universities should expand current guidelines for ChatGPT use by encouraging students to critically engage with the AI's responses. For example, alongside existing instructions on using ChatGPT for writing assistance, students should be advised to challenge and critically evaluate the AI's outputs. Educational materials should emphasize that students can and should question ChatGPT's answers, especially in areas requiring critical thinking or nuanced understanding.

More importantly, universities should organize workshops that focus specifically on the ethical implications of using AI in academic settings. These workshops could cover topics like plagiarism, academic integrity, and the responsible use of AI tools. Through case studies and interactive discussions, students can explore real-world scenarios that highlight both the positive applications and potential pitfalls of using ChatGPT.

OpenAI (and other LLM providers) could include an 'education mode' provided to universities which provides certain features such as: (i) transparency notices in its responses, especially when dealing with complex or sensitive topics. For example, adding disclaimers like, "This response is based on information that may be outdated or incomplete" can remind students that AI-generated content should not be taken at face value. (ii) automatically flagging potentially problematic interactions, such as repeated attempts to get direct answers for assignments, (iii) Encourage students to reflect on their interactions with ChatGPT by maintaining a log of their queries and reviewing them periodically. Reflection prompts such as "Did ChatGPT help you understand this topic better?" or "What other ways could you have approached this question?" could be integrated into the learning process, fostering self-awareness and critical thinking skills.

## 7 Limitations and Future Work

This study utilizes deeply personal data obtained through a data donation model, prioritizing the privacy and anonymity of student participants. While conducting follow-up interviews could have enriched the analysis by providing additional context and deeper insights into the interactions, we deliberately chose to forgo this approach to protect participants' confidentiality. This commitment to privacy is central to our research design, though it does present certain limitations.

One key limitation of our study is the potential for sampling bias inherent in the data donation model. As participation is voluntary, there is a likelihood of self-selection, where individuals who choose to contribute their data may differ in meaningful ways from those who do not, despite efforts to emphasize the anonymity and security of the process. This could result in an underrepresentation of certain user behaviors or demographics, limiting the generalizability of the findings.

Regarding future work, the data donation model offers a scalable and flexible approach that preserves participant privacy, making it a promising method for expanding this research. Although our current study involves a relatively small sample size, the model can be extended to multiple sites and institutions, allowing for broader data collection across diverse student populations. Scaling the data donation model could provide a more comprehensive understanding of ChatGPT usage patterns, capturing a wider range of interactions and contexts.

There is significant potential for future studies to leverage this approach across various educational settings, enhancing the robustness and applicability of the findings. Expanding this work could facilitate comparative analyses between different academic institutions, disciplines, and student demographics, providing deeper insights into the evolving role of AI in education. Ultimately, our model not only safeguards privacy but also opens new avenues for large-scale research on human-LLM interactions, contributing valuable knowledge to the field of HCI and beyond.

## 8 Conclusion

With the proliferation of ChatBots and Large Language Models like GPT, there is a need for a more thorough understanding of the use Generative AI system in everyday life. In this study, we use mixed methods to analyze the digital archives of thirty six undergraduate students to analyze their use of ChatGPT. We problematize and unpack the different ways in which students use ChatGPT to generate essays and access information. We also discuss more dynamic information access scenarios including the use of ChatGPT to generate and learn how to create computer code in different languages. We discuss the parasocial relationship between our respondents and ChatGPT as well as how it changed over time, especially in regards to conversational repair processes. We reflect on how our findings build on earlier work in human-chatBot interactions and provide design recommendations for better interactions with ChatBots.

## References


[1] Benicio Gonzalo Acosta-Enriquez, Marco Agustín Arbulú Ballesteros, Olger Huamaní Jordan, Carlos López Roca, and Karina Saavedra Tirado. 2024. Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: effect of intent to use, verification of information and responsible use. *BMC psychology* 12, 1 (2024), 255.

[2] Dimo Angelov. 2020. Top2Vec: Distributed Representations of Topics. (Aug. 2020). https://doi.org/10.48550/arXiv.2008.09470

[3] Lateef Ayinde, Muhamad Prabu Wibowo, Benhur Ravuri, and Forhan Bin Emdad. 2023. ChatGPT as an important tool in organizational management: A review of the literature. *Business Information Review* 40, 3 (2023), 137–149.

[4] David Baidoo-Anu and Leticia Owusu Ansah. 2023. Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI* 7, 1 (2023), 52–62.

[5] Feni Betriana, Kyoko Osaka, Kazuyuki Matsumoto, Tetsuya Tanioka, and Rozzano C Locsin. 2021. Relating Mori's Uncanny Valley in generating conversations with artificial affective communication and natural language processing. *Nursing Philosophy* 22, 2 (2021), e12322.

[6] Wiebe E Bijker and John Law. 1994. *Shaping technology/building society: Studies in sociotechnical change.* MIT press.

[7] Som S Biswas. 2023. Role of chat gpt in public health. *Annals of biomedical engineering* 51, 5 (2023), 868–869.

[8] Petter Bae Brandtzaeg and Asbjørn Følstad. 2018. Chatbots: changing user needs and motivations. *interactions* 25, 5 (2018), 38–43.

[9] Ricardo J. G. B. Campello, Davoud Moulavi, and Joerg Sander. 2013. Density-Based Clustering Based on Hierarchical Density Estimates. In *Advances in Knowledge Discovery and Data Mining (Lecture Notes in Computer Science)*, Jian Pei, Vincent S. Tseng, Longbing Cao, Hiroshi Motoda, and Guandong Xu (Eds.). Springer, Berlin, Heidelberg, 160–172. https://doi.org/10.1007/978-3-642-37456-2_14

[10] Ana Paula Chaves and Marco Aurelio Gerosa. 2021. How should my chatbot interact? A survey on social characteristics in human–chatbot interaction design. *International Journal of Human–Computer Interaction* 37, 8 (2021), 729–758.

[11] Laura Coffey. 2024. New ChatGPT Zeroes In on Higher Ed. *Inside Higher Ed* (May 31 2024). https://www.insidehighered.com/news/tech-innovation/artificial-intelligence/2024/05/31/new-chatgpt-zeroes-higher-ed Accessed: 2024-09-12.

[12] Kathleen MT Collins. 2010. Advanced sampling designs in mixed research. *Sage handbook of mixed methods in social and behavioral research* (2010), 353–377.

[13] Cammy Crolic, Felipe Thomaz, Rhonda Hadi, and Andrew T Stephen. 2022. Blame the bot: Anthropomorphism and anger in customer–chatbot interactions. *Journal of Marketing* 86, 1 (2022), 132–148.

[14] G Currie, C Singh, T Nelson, C Nabasenja, Y Al-Hayek, and K Spuur. 2023. ChatGPT in medical imaging higher education. *Radiography* 29, 4 (2023), 792–799.

[15] Roy De Kleijn, Lisa van Es, George Kachergis, and Bernhard Hommel. 2019. Anthropomorphization of artificial agents leads to fair and strategic, but not altruistic behavior. *International Journal of Human-Computer Studies* 122 (2019), 168–173.

[16] Johan Oswin De Nieva, Jose Andres Joaquin, Chaste Bernard Tan, Ruzel Khyvin Marc Te, and Ethel Ong. 2020. Investigating students' use of a mental health chatbot to alleviate academic stress. In *6th International ACM In-Cooperation HCI and UX Conference*. 1–10.

[17] Massimiliano Dibitonto, Katarzyna Leszczynska, Federica Tazzi, and Carlo M Medaglia. 2018. Chatbot in a campus environment: design of LiSA, a virtual assistant to help students in their university life. In *Human-Computer Interaction. Interaction Technologies: 20th International Conference, HCI International 2018, Las Vegas, NV, USA, July 15–20, 2018, Proceedings, Part III 20*. Springer, 103–116.

[18] Hoa Dinh and Thien Khai Tran. 2023. EduChat: An AI-based chatbot for university-related information using a hybrid approach. *Applied Sciences* 13, 22 (2023), 12446.

[19] Michael Dowling and Brian Lucey. 2023. ChatGPT for (finance) research: The Bananarama conjecture. *Finance Research Letters* 53 (2023), 103662.

[20] Harry Barton Essel, Dimitrios Vlachopoulos, Akosua Tachie-Menson, Esi Eduafua Johnson, and Papa Kwame Baah. 2022. The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. *International Journal of Educational Technology in Higher Education* 19, 1 (2022), 57.

[21] Ashleigh A Farmer, Bennett Lange, Shannon Kim, Suhrud Pathak, Sibi Chakravarthy, Jack Deruiter, K Reeta Vijayarani, Akila Ramanathan, Hanan Fahad Alharbi, and Muralikrishnan Dhanasekaran. 2024. Artificial Intelligence (AI) and Its Role in Depression. In *Application of Artificial Intelligence in Neurological Disorders*. Springer, 63–85.

[22] Tira Nur Fitria. 2023. Artificial intelligence (AI) technology in OpenAI ChatGPT application: A review of ChatGPT in writing English essay. In *ELT Forum: Journal of English Language Teaching*, Vol. 12. 44–58.

[23] Kathleen Kara Fitzpatrick, Alison Darcy, and Molly Vierhile. 2017. Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): a randomized controlled trial. *JMIR mental health* 4, 2 (2017), e7785.

[24] Asbjørn Følstad, Theo Araujo, Effie Lai-Chong Law, Petter Bae Brandtzaeg, Symeon Papadopoulos, Lea Reis, Marcos Baez, Guy Laban, Patrick McAllister, Carolin Ischen, et al. 2021. Future directions for chatbot research: an interdisciplinary research agenda. *Computing* 103, 12 (2021), 2915–2942.

[25] Luke K Fryer, Mary Ainley, Andrew Thompson, Aaron Gibson, and Zelinda Sherlock. 2017. Stimulating and sustaining interest in a language course: An experimental comparison of Chatbot and Human task partners. *Computers in human behavior* 75 (2017), 461–468.

[26] Barney Glaser and Anselm Strauss. 2017. *Discovery of grounded theory: Strategies for qualitative research.* Routledge.

[27] Anjana Gosain and Saanchi Sardana. 2017. Handling class imbalance problem using oversampling techniques: A review. In *2017 international conference on advances in computing, communications and informatics (ICACCI)*. IEEE, 79–85.

[28] Simone Grassini. 2023. Shaping the future of education: exploring the potential and consequences of AI and ChatGPT in educational settings. *Education Sciences* 13, 7 (2023), 692.

[29] Stephanie Greer, Danielle Ramo, Yin-Juei Chang, Michael Fu, Judith Moskowitz, Jana Haritatos, et al. 2019. Use of the chatbot "vivibot" to deliver positive psychology skills and promote well-being among young people after cancer treatment: randomized controlled feasibility trial. *JMIR mHealth and uHealth* 7, 10 (2019), e15018.

[30] Maarten Grootendorst. 2022. BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794* (2022).

[31] Greg Guest, Arwen Bunce, and Laura Johnson. 2006. How many interviews are enough? An experiment with data saturation and variability. *Field methods* 18, 1 (2006), 59–82.

[32] Jieun Han, Haneul Yoo, Junho Myung, Minsun Kim, Tak Yeon Lee, So-Yeon Ahn, and Alice Oh. 2024. RECIPE4U: Student-ChatGPT Interaction Dataset in EFL Writing Education. *arXiv preprint arXiv:2403.08272* (2024).

[33] Songhee Han and Min Kyung Lee. 2022. FAQ chatbot and inclusive learning in massive open online courses. *Computers & Education* 179 (2022), 104395.

[34] Jennifer Hill, W Randolph Ford, and Ingrid G Farreras. 2015. Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations. *Computers in human behavior* 49 (2015), 245–250.

[35] Sebastian Hobert. 2019. How are you, chatbot? evaluating chatbots in educational settings–results of a literature review. (2019).

[36] Mohit Jain, Pratyush Kumar, Ramachandra Kota, and Shwetak N Patel. 2018. Evaluating and informing the design of chatbots. In *Proceedings of the 2018 designing interactive systems conference*. 895–906.

[37] Varsha Jain, Himanshu Rai, Parvathy Parvathy, and Emmanuel Mogaji. 2023. The prospects and challenges of ChatGPT on marketing research and practices. *Emmanuel, The Prospects and Challenges of ChatGPT on Marketing Research and Practices (March 23, 2023)* (2023).

[38] D Jishnu, Malini Srinivasan, Gondi Surender Dhanunjay, and R Shamala. 2023. Unveiling student motivations: A study of ChatGPT usage in education. *ShodhKosh: Journal of Visual and Performing Arts* 4, 2 (2023), 65–73.

[39] Nam Wook Kim, Hyung-Kwon Ko, Grace Myers, and Benjamin Bach. 2024. ChatGPT in Data Visualization Education: A Student Perspective. *arXiv preprint arXiv:2405.00748* (2024).

[40] Mohammad Amin Kuhail, Nazik Alturki, Salwa Alramlawi, and Kholood Alhejori. 2023. Interacting with educational chatbots: A systematic review. *Education and Information Technologies* 28, 1 (2023), 973–1018.

[41] Jonna Lee and Meryem Yilmaz Soylu. 2023. ChatGPT and assessment in higher education. *An interview with A. Goel and S. Harmon. Centre for 21st Century Universities* (2023).

[42] Chi-Hsun Li, Su-Fang Yeh, Tang-Jie Chang, Meng-Hsuan Tsai, Ken Chen, and Yung-Ju Chang. 2020. A conversation analysis of non-progress and coping strategies with a banking task-oriented chatbot. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–12.

[43] Bingjie Liu and S Shyam Sundar. 2018. Should machines express sympathy and empathy? Experiments with a health advice chatbot. *Cyberpsychology, Behavior, and Social Networking* 21, 10 (2018), 625–636.

[44] Qi Lu, Yuan Yao, Longhai Xiao, Mingzhu Yuan, Jue Wang, and Xinhua Zhu. 2024. Can ChatGPT effectively complement teacher assessment of undergraduate students' academic writing? *Assessment & Evaluation in Higher Education* (2024), 1–18.

[45] Ewa Luger and Abigail Sellen. 2016. "Like Having a Really Bad PA": The Gulf between User Expectation and Experience of Conversational Agents. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 5286–5297. https://doi.org/10.1145/2858036.2858288

[46] Takuya Maeda and Anabel Quan-Haase. 2024. When Human-AI Interactions Become Parasocial: Agency and Anthropomorphism in Affective Design. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*. 1068–1077.

[47] Julia M Markel, Steven G Opferman, James A Landay, and Chris Piech. 2023. Gpteach: Interactive ta training with gpt-based students. In *Proceedings of the tenth acm conference on learning@ scale*. 226–236.

[48] Nora McDonald, Sarita Schoenebeck, and Andrea Forte. 2019. Reliability and inter-rater reliability in qualitative research: Norms and guidelines for CSCW and HCI practice. *Proceedings of the ACM on human-computer interaction* 3, CSCW (2019), 1–23.

[49] Lenin Medeiros, Tibor Bosse, and Charlotte Gerritsen. 2021. Can a chatbot comfort humans? Studying the impact of a supportive chatbot on users' self-perceived stress. *IEEE Transactions on Human-Machine Systems* 52, 3 (2021), 343–353.

[50] Lenin Medeiros, Charlotte Gerritsen, and Tibor Bosse. 2019. Towards humanlike chatbots helping users cope with stressful situations. In *Computational Collective Intelligence: 11th International Conference, ICCCI 2019, Hendaye, France, September 4–6, 2019, Proceedings, Part I 11*. Springer, 232–243.

[51] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient Estimation of Word Representations in Vector Space. *arXiv:1301.3781 [cs]* (Jan. 2013). http://arxiv.org/abs/1301.3781 arXiv: 1301.3781.

[52] Carlos Montemayor, Jodi Halpern, and Abrol Fairweather. 2022. In principle obstacles for empathic AI: why we can't replace human empathy in healthcare. *AI & society* 37, 4 (2022), 1353–1359.

[53] Harris Bin Munawar and Nikolaos Misirlis. 2024. ChatGPT in Classrooms: Transforming Challenges into Opportunities in Education. *arXiv preprint arXiv:2405.10645* (2024).

[54] Daye Nam, Andrew Macvean, Vincent Hellendoorn, Bogdan Vasilescu, and Brad Myers. 2024. Using an llm to help with code understanding. In *Proceedings of the IEEE/ACM 46th International Conference on Software Engineering*. 1–13.

[55] OpenAI. 2024. ChatGPT. https://openai.com/chatgpt. Accessed: 2024-09-12.

[56] OpenAI. 2024. Introducing ChatGPT for Educators. https://openai.com/introducing-chatgpt-edu. Accessed: 2024-09-12.

[57] Dong-Min Park, Seong-Soo Jeong, and Yeong-Seok Seo. 2022. Systematic review on chatbot techniques and applications. *Journal of Information Processing Systems* 18, 1 (2022), 26–47.

[58] John V Pavlik. 2023. Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education. *Journalism & mass communication educator* 78, 1 (2023), 84–93.

[59] Diana Pérez-Marín and Ismael Pascual-Nieto. 2013. An exploratory study on how children interact with pedagogic conversational agents. *Behaviour & Information Technology* 32, 9 (2013), 955–964.

[60] Md Mostafizer Rahman and Yutaka Watanobe. 2023. ChatGPT for education and research: Opportunities, threats, and strategies. *Applied Sciences* 13, 9 (2023), 5783.

[61] Amon Rapp, Lorenzo Curti, and Arianna Boldi. 2021. The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots. *International Journal of Human-Computer Studies* 151 (2021), 102630.

[62] Partha Pratim Ray. 2023. ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet of Things and Cyber-Physical Systems* 3 (2023), 121–154.

[63] Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. (Aug. 2019). https://doi.org/10.48550/arXiv.1908.10084

[64] Michael Röder, Andreas Both, and Alexander Hinneburg. 2015. Exploring the Space of Topic Coherence Measures. In *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining (WSDM '15)*. ACM, New York, NY, USA, 399–408. https://doi.org/10.1145/2684822.2685324 event-place: Shanghai, China.

[65] Reijo Savolainen. 1995. Everyday life information seeking: Approaching information seeking in the context of "way of life". *Library & information science research* 17, 3 (1995), 259–294.

[66] Sudhansh Sharma and Ramesh Yadav. 2022. Chat GPT–A technological remedy or challenge for education system. *Global Journal of Enterprise Information System* 14, 4 (2022), 46–51.

[67] Bayan Abu Shawar and Eric Atwell. 2007. Chatbots: are they really useful? *Journal for Language Technology and Computational Linguistics* 22, 1 (2007), 29–49.

[68] Abdulhadi Shoufan. 2023. Exploring students' perceptions of ChatGPT: Thematic analysis and follow-up survey. *IEEE Access* 11 (2023), 38805–38818.

[69] Marita Skjuve, Asbjørn Følstad, Knut Inge Fostervold, and Petter Bae Brandtzaeg. 2022. A longitudinal study of human–chatbot relationships. *International Journal of Human-Computer Studies* 168 (2022), 102903.

[70] Artur Strzelecki. 2023. To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive learning environments* (2023), 1–14.

[71] Miriam Sullivan, Andrew Kelly, and Paul McLaughlan. 2023. ChatGPT in higher education: Considerations for academic integrity and student learning. (2023).

[72] Betty Tärning and Annika Silvervarg. 2019. "I didn't understand, I´ m really not very smart"—how design of a digital tutee's self-efficacy affects conversation and student behavior in a digital math game. *Education Sciences* 9, 3 (2019), 197.

[73] Jörg Von Garrel and Jana Mayer. 2023. Artificial Intelligence in studies—use of ChatGPT and AI-based tools among students in Germany. *humanities and social sciences communications* 10, 1 (2023), 1–9.

[74] Katja Wagner, Frederic Nimmermann, and Hanna Schramm-Klein. 2019. Is it human? The role of anthropomorphism as a driver for the successful acceptance of digital voice assistants. (2019).

[75] Rui Wang, Hongsong Feng, and Guo-Wei Wei. 2023. ChatGPT in Drug Discovery: A Case Study on Anticocaine Addiction Drug Development with Chatbots. *Journal of chemical information and modeling* 63, 22 (2023), 7189–7209.

[76] Xuan Wang and Ryohei Nakatsu. 2013. How do people talk with a virtual philosopher: log analysis of a real-world application. In *Entertainment Computing–ICEC 2013: 12th International Conference, ICEC 2013, São Paulo, Brazil, October 16-18, 2013. Proceedings 12*. Springer, 132–137.

[77] Kevin Warwick and Huma Shah. 2015. Human misidentification in Turing tests. *Journal of Experimental & Theoretical Artificial Intelligence* 27, 2 (2015), 123–135.

[78] Joel Wester, Tim Schrills, Henning Pohl, and Niels van Berkel. 2024. "As an AI language model, I cannot": Investigating LLM Denials of User Requests. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–14.

[79] David Westerman, Aaron C Cross, and Peter G Lindmark. 2019. I believe in a thing called bot: Perceptions of the humanness of "chatbots". *Communication Studies* 70, 3 (2019), 295–312.

[80] Ramazan Yilmaz and Fatma Gizem Karaoglan Yilmaz. 2023. Augmented intelligence in programming learning: Examining student views on the use of ChatGPT for programming learning. *Computers in Human Behavior: Artificial Humans* 1, 2 (2023), 100005.

[81] Jennifer Zamora. 2017. I'm Sorry, Dave, I'm Afraid I Can't Do That: Chatbot Perception and Expectations. In *Proceedings of the 5th International Conference on Human Agent Interaction* (Bielefeld, Germany) *(HAI '17)*. Association for Computing Machinery, New York, NY, USA, 253–260.

https://doi.org/10.1145/3125739.3125766
[82] Erin Zaroukian, Jonathan Z Bakdash, Alun Preece, and Will Webberley. 2017. Automation Bias with a Conversational Interface. In *IEEE International InterDisciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)*.
[83] Ruofei Zhang, Di Zou, and Gary Cheng. 2023. A review of chatbot-assisted learning: pedagogical approaches, implementations, factors leading to effectiveness, theories, and future directions. *Interactive Learning Environments* (2023), 1–29.
[84] Yan Zhang and Barbara M Wildemuth. 2009. Unstructured interviews. *Applications of social research methods to questions in information and library science* 2 (2009), 222–231.

## 9 Appendix

Table 4 shows the classifier results on all the categories and subcategories. Only categories and subcategories where the performance was satisfactory are being shown.

Table 4. Predicted category, prediction model metrics.

| **Category** | **Accuracy** | **Precision** | **Recall** | **F1** | **AUC ROC** |
|---|---|---|---|---|---|
| Content Generation | 0.903 | 0.920 | 0.956 | 0.938 | 0.843 |
| Information Seeking | 0.916 | 0.928 | 0.976 | 0.951 | 0.785 |
| Students' Interaction with ChatGPT | 0.910 | 0.950 | 0.872 | 0.909 | 0.911 |
| ChatGPT's Response | 0.821 | 0.205 | 0.708 | 0.318 | 0.768 |
| Student Interaction with ChatGPT → students' positive feedback towards ChatGPT's answer | 0.929 | 0.289 | 0.846 | 0.431 | 0.889 |
| Information Seeking → academic content → questions on the coding errors | 0.917 | 0.279 | 0.800 | 0.414 | 0.861 |
| Information Seeking → academic content → ask Chat GPT to critique students' essay | 0.919 | 0.029 | 1.000 | 0.057 | 0.959 |
| ChatGPT's Response → apologizing for previous response | 0.838 | 0.178 | 0.684 | 0.283 | 0.765 |
| ChatGPT's Response → misunderstanding students' commands | 0.914 | 0.162 | 0.600 | 0.255 | 0.761 |
| Content Generation → multiple choices and filling blank questions | 0.701 | 0.951 | 0.658 | 0.778 | 0.763 |

Table 5 shows the results from applying our classifier on the qualitative coding (Q, Section 4.1) and BERTopic (B, Section 4.3).

Table 5. Total categories from qualitative analysis (Q) and BERTopic topic modeling (B).

| **Category** | **#** | **Frac.** | **Source** |
|---|---|---|---|
| Information Seeking | 9,010 | 0.855 | Q |
| Content Generation | 8,213 | 0.780 | Q |
| Student ChatGPT Interaction | 5,217 | 0.495 | Q |
| Science, Technology and Management | 3,005 | 0.285 | B |
| Coding | 2,608 | 0.248 | B |
| Social Science and Humanities | 2,514 | 0.239 | B |
| Math | 1,241 | 0.118 | B |
| Content Generation → multiple choices and filling in blanks questions | 1,188 | 0.113 | Q |
| Computer Science | 512 | 0.049 | B |
| ChatGPT's Response | 445 | 0.042 | Q |
| Chatgpt's Response → apologizing for previous response | 351 | 0.033 | Q |
| Student Interaction with ChatGPT → asking to rewrite student text | 337 | 0.032 | Q |
| Information Seeking → questions on coding error | 226 | 0.021 | Q |
| ChatGPT's Response → repairing misunderstandings | 216 | 0.021 | Q |
| Information Seeking → critique student essay | 212 | 0.020 | Q |
| Student Interaction with ChatGPT → casual talk | 193 | 0.018 | Q |
| Internship | 177 | 0.017 | B |
| Student Interaction with ChatGPT → Student's positive feedback towards ChatGPT | 159 | 0.015 | Q |
| Music | 143 | 0.014 | B |
| Synonym | 98 | 0.009 | B |
| Email | 97 | 0.009 | B |
| Polite | 75 | 0.007 | B |
| Financial | 55 | 0.005 | B |
| Citation | 47 | 0.004 | B |