Analysing Student Engagement with Large Language Models in Higher Education: Prompts as Channels of Communication with AI

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Table of contents

List of Figures

Abstract

Background

The aim of this study is to establish concrete insights into the ways in which students in higher education are engaging with large language models (LLM) through an analysis of the prompts they have written. Integrating frameworks from Human-Machine Communication (HMC) studies and student engagement literature, this research intends on elucidating prompts as a valuable source of analysis for the effect that LLMs have on students' approaches to their academic work. These findings will inform scholarly perspectives on the precise strategies, participations and mannerisms students employ within their communications with LLMs.

Method

This research utilises a questionnaire to collect samples of conversations and individual prompts from students' interaction with LLMs in academic contexts. It also asks for their academic background, such as what programme they enrolled in and previous areas of academic expertise. It analyses over 800 prompts from 23 students in higher education within the United Kingdom.

Analysis of this data employed an integrative approach, relating Guzman and Lewis's (2022) framework for human-AI communications with dimensions of student engagement. This approach enables the analysis of prompt data not only within its specific context as a unique mode of communication with a technological entity but also sheds light on the pedagogical implications of these interactions.

Results

The results from this study presents four main types of engagement with large language models from students in higher education: linguistic manipulation, engagement with corpus data, controlling the LLM and ideation. These engagements reveal how students are mostly benefitting from the LLM's ability to reword large bodies of text into different styles of language, as well as the ability to navigate the corpus data as a resource for information. Students also utilised LLMs to generate responses that would assist with the exploration of new ideas, as well as the evaluation of ideas. A large portion of prompts were also employed to control the LLM, directing the LLM to respond in certain ways or attempting to fix the LLM's interpretation of previous prompts.

Glossary

Term	Definition	Abbreviation
Artificial Intelligence	Technology capable of intelligent behaviour, typically involving tasks that would require human intelligence such as visual perception, speech recognition, decision-making, and language translation	AI
Artificial Intelligence in Education	The application of AI technologies to educational contexts	AIED
Large Language Model	A type of AI model that processes and generates human-like text based on enormous datasets of existing text. These models can understand and generate languages, making them useful for applications like chatbots, translation, and content creation.	LLM
Corpus Data	The large collection of text data used to train the model, enabling it to generate and understand human-like language based on the patterns and information present in that dataset.	
Natural Language Processing	A learnt capability of LLMs to process and generate language that appears natural.	NLP
Human-Machine Communication	The study of how humans communicate with automated systems and machines, including the implications and dynamics of these interactions within various contexts.	HMC

Human-AI Communication:	A branch of HMC centred on communications between humans and AI subjects.	HAIC
Input Data	WIthin LLMs, this refers to the text data that is entered into a system for processing.	
Student Centred Learning	An educational approach that emphasises students' roles in proactive management of their own learning and independent knowledge construction.	SCL

Introduction

Large Language Models in Higher Education

Large language models (LLMs) are a class of artificial intelligence models designed to interpret and generate natural language through Natural Language Processing (NLP). The accessibility of these models requires an internet connection and a compatible device for web browsing. Popular models in use today include OpenAI's ChatGPT, Anthropic's Claude, Google's Gemini, and Meta's LLama. These models are often available as a platform for conversation between the user and a chatbot. They work by inputting a prompt and receiving a generated text response, which attempts to deliver an appropriate answer to the prompt. In brief, the LLM functions by analysing the input text, predicting the next words in a sequence based on learned patterns from vast amounts of data, and constructing a coherent and contextually relevant response.

The proliferation of big data companies and the continuous development of methods to utilise this data has made data a valuable resource in the modern world (Palmer, 2006). The growing significance of data has fueled the advancement of AI technologies, which increasingly depend on this data for their development. This paradigm is mirrored in the educational sector, where Crompton and Burke (2023) and Chu et al. (2022) document the rapid rise of AI applications in higher education over the past five years, highlighting how publications on this topic in educational journals increased by nearly threefold in 2021 and 2022 compared to prior years. AI has continued to be adopted as a versatile tool across a wide variety of educational disciplines such as language education (Liang et al., 2021), medical

education (Winkler-Schwartz et al., 2019), mathematics (Hwang & Tu, 2021), and engineering (Shukla et al., 2019).

Outside of institutional adoptions, the use of LLMs within student populations in higher education is predominantly characterised by a bottom-up approach, independently driven by students' autonomous decisions rather than external pressures by institutional bodies. Huang (2023) reports the widespread adoption of ChatGPT specifically among higher education students, revealing how institutions have found it challenging to regulate this adoption due to its self-initiated nature and the rapid rate at which it has been embraced as an educational tool. According to a survey from BestColleges (Welding, 2024), 61% of higher education students believe AI tools like ChatGPT will become the new norm. Accordingly, Dai et al. (2023) theorises that, as of 2024, the student user base of LLM tools has reached a certain threshold of adoption, such that LLM usage is being self-sustained by student peer networks, embedding them as familiar tools for the future of university students' academic processes.

The Underlying Issues with Rapid Student Adoption

Newport (2016) states that "[w]ithout clear feedback on the impact of various behaviours to the bottom line, we will tend towards behaviours that are easiest in the moment' ' (Newport 2016, pp. 58). Similarly, a study from the Journal of Library and Information Sciences (Connaway et al., 2011) suggests that information seekers often prioritise convenience over content, indicating that convenience is a primary criterion in this process. This finding is particularly relevant to students in higher education, who frequently assume the role of information seekers within knowledge repositories such as libraries. Thus, with the increasing accessibility of LLMs for students in higher education, there is a growing likelihood that students will increasingly rely on these tools for academic tasks. As highlighted by Chu et al. (2022), students are adopting this technology at an unprecedented rate. Moreover, Oh and Reeves (2014) emphasises that while new generation students rapidly adopt technology, the speed of transition in both research and educational practice is significantly slower, which exacerbates concerns about students' problematic engagement with technology and the excessive time they devote to it. Despite its rapid integration, only 23% of UK teachers feel equipped to transition to an AI-enabled classroom (Oxford University Press, 2023), and there is a limited understanding of technology usage among the faculty of educational policies (Habib & Johannesen, 2014). Furthermore, higher education institutions are still in the early stages of developing comprehensive strategies to effectively integrate the influx of AI tools provided by private companies into their curricula and administrative frameworks (Pedró, 2019).

Looking Towards Student Engagements with LLMs

Given the rapid adoption and nascent nature of LLMs in higher education (Chu. et al., 2022), coupled with a notable gap within institution's understanding of new technologies (Oh and Reeves, 2014), this paper aims to achieve a focused study on students' engagements with LLMs. By analysing these engagements—the ways students utilise the affordances of the technology—the broader impact

these tools have on users can be better understood. Studying LLMs in this manner within higher education responds to an identified research void by scholars like Hrastinski et al. (2019) and Zawacki-Richter et al. (2019), who point out the lack of detailed understanding of AI's collective advantages in this field. This exploration is essential to refine teaching practices and to enhance student engagement and outcomes, aligning with the longstanding academic calls for a more profound understanding of the influence of educational technology (Castañeda & Selwyn, 2018) (Krause & Coates, 2008) (Nelson Laird & Kuh, 2005). When educational institutions and their practitioners fully comprehend the advantages these technologies offer and understand the reasons behind their usage by students, they can more effectively manage and guide their application in educational settings. Moreover, a comprehensive grasp of these tools fosters a mutual understanding between educators and students, which is vital due to existing knowledge gaps among educational policy faculty members (Habib & Johannesen, 2014). Understanding technological affordances also clarifies students' perceptions of source credibility and risks of use associated with LLMs, significantly impacting their approach to utilising these tools. This detailed understanding helps predict long-term effects on user behaviour and educational outcomes, thereby providing insights into both the benefits and challenges posed by the adoption of LLM tools in educational settings. Studying the engagements students have with LLM tools is essential to address their rapid adoption, assess how ease of use may overshadow depth of learning, support unprepared teachers, and guide the strategic integration of these recent technologies in higher education.

Analysing Students' Prompts

As the adoption of LLMs by students in higher education grows, so too does the volume of prompts they write. This research aims to centre these instances of communication as windows into the pedagogical implications of LLMs as educational tools within higher education. Drawing upon Human Machine Communication (HMC) studies and theories of student engagement, this research analyses prompts from students in higher education within the United Kingdom. Despite the growing prevalence of chatbots and similar communicative technologies in recent years (Wiederhold, 2021), advanced LLMs have only recently become widely accessible and rapidly embraced. Croes and Antheunis (2021) and Weidmüller (2022) argue that earlier research in HMC has struggled to produce generalisable results due to novelty effects impacting the initial interactions studied. This research offers a contemporary examination of communicative technologies by analysing interactions from a cohort of higher education students in the United Kingdom, some of whom have developed both proficiency and experience with these advanced tools. An integrated approach, utilising Guzman and Lewis's (2022) Human-AI Communication (HAIC) framework as well as dimensions of student engagement, is used to analyse each prompt to determine the students' specific methods of engagement with the LLM. Understanding how higher education students utilise LLMs in their academic work will make the realities of LLM usage

transparent to educators and policymakers, ensuring they remain informed and aligned with the latest developments in AI technology.

This analysis provides insights into the methods of engagement that students employ within their use of LLMs for their academic work, as well as recommendations for institutional responses towards this influx of LLM usage. The findings help address and elucidate the specific strategies and mannerisms that students are adopting with LLMs to assist with their academic work. The discussion considers the pedagogical advantages and disadvantages that such strategies might incur on students' learning. Ultimately, this research aims to contribute its findings and insights from its direct analysis of prompts into broader educational literature on institutional responses towards the rise of AI technologies in education.

Literature Review

The Upwards Trend and Contested Role of AI in Higher Education

This growing popularity and perceived advantages of LLMs have led to a surge of optimism within certain educational literature for the implementation of AI technology in practices of education. Praise for LLMs frequently emphasise their efficacy in engaging with the principles of student-centred learning (SCL). Students' adoption of LLMs in higher education is fostering several key behaviours and values of SCL, including personalised learning, increased engagement and enhanced autonomy allowing students to control their learning process (Lee and Hannafin 2016) (Klemenčič, 2017). Chen et al. (2020), Crompton et al. (2020) and Crompton and Song (2021) support this by reporting on AI technologies' abilities to personalise instruction to meet diverse learner needs (Verdú et al., 2017); facilitate self-directed learning (Rudolph et al., 2023); and support student-centred constructions of knowledge (Kasneci et al., 2023). Intelligent Tutoring Systems (ITS) are another notable example of student-centred LLM applications in education. Alam (2023) and Chowdhury et al. (2024) both claim that LLMs can author ITSs which can provide personalised learning experiences for students similar to one-on-one tutoring. Student-focused AI in Education (AIED) research aims to investigate the learning gains that transpire in the absence of direct involvement of human teachers. These gains are typically measured through pre-test and post-test experiments, showing measurable improvements in student knowledge (Wang et al., 2024) (Verdú et al., 2017). The adoption of LLMs and ITS in educational settings reflects a trend towards student-centred pedagogies, focusing on catering to individual learning preferences and leveraging students' intrinsic motivations.

Although numerous studies support an optimistic view of the role of LLMs in education, there are substantial grounds for scepticism and caution. As mentioned before, these studies commonly employ pre- and post-test methods to evaluate the effectiveness of instructional interventions. However, the inherent limitations of such methodologies—including potential confounding variables, learning effects, and often the absence of control groups—necessitate a careful interpretation of these results. Additionally, the focus on measurable improvements can lead to an emphasis on teaching to tests, a trend evident in many well-established AIED systems (Knox, 2020). This approach can widen achievement gaps and systematically under-prepare marginalised students who lack access to new technologies, hindering their readiness for higher education and competitive job markets (Styron and Styron, 2012). The difficulties in measuring the effectiveness of instructional methods underscore the complexities associated with integrating AI into educational settings. Dai et al. (2023) acknowledge LLMs' potential to enhance SCL but caution against the lack of accountability and transparency in AI development. Long and Magerko (2020) stress the importance of thorough scrutiny in assessing the ethical, social, and practical impacts of AI technologies, particularly noting the challenges at the nascent stages of development. They caution that an excessive reliance on AI could degrade cognitive skills and diminish student motivation. Ahmad et al. (2023) raise additional concerns about the erosion of decision-making skills, increased laziness, and security risks, which collectively signal the growing dependency on AI within the educational sector and the urgent need for critical evaluations of its long-term impacts. These deficiencies contribute to the broader concerns (Long and Magerko, 2020) (Morales-García et al., 2024) regarding the displacement of an inadequately prepared future workforce by AI. The inherent issues and future implications of integrating AI tools in higher education are prominently discussed in AIED literature, with significant attention given to the long-term effects of student usage of these tools. Therefore, a comprehensive understanding of how students are engaging with AI tools in higher education can inform our response to their increasing prevalence. In the case of LLMs, engagement predominantly occurs through prompts, necessitating a detailed examination of this interaction to understand its implications fully.

Examining Student Engagement with LLMs

Kuh et al. (2008) define student engagement as ‘the time and energy students invest in educationally purposeful activities and the effort institutions devote to using effective educational practices’ (pp. 542). Similarly, Newmann et al. (1992) describes engagement in academic work as the ‘student’s psychological investment in and effort directed toward learning, understanding, mastering the knowledge, skills or crafts that the academic work is intended to promote’ (pp. 12). Emerging technologies such as LLMs, which possess generative capabilities activated through natural language prompts, represent substantial shifts in how students in higher education allocate their time and energy towards mastering the knowledge, skills, and crafts imparted by academic work. Student engagement

theory is characterised by a multifaceted array of interrelated and overlapping dimensions of certain types of observable behaviours within students (Fredricks et al. 2016). Empirical analysis of student engagement typically explores several dimensions, including cognitive, agentic, social, and behavioural aspects (Reeve, 2012) (Fredericks et al., 2004). Moreover, this concept has been extensively researched across various contexts spanning students' long term institutional engagements, students' attention in schools and classrooms settings and momentary interaction within specific learning activities (Skinner & Pitzer, 2012). This study focuses on the latter, analysing students' engagement within the transactional exchanges they have with LLMs across their academic work.

Prompts as Modes of Human-Machine Communication in Higher Education

Every instance of computer usage entails a mode of communication—a distinct pattern governing how users interact with the system. HMC studies investigates how humans interact with machines using languages, symbols, or other forms of communication. This concept has evolved significantly, from early command-line interfaces to the direct manipulation of on-screen visuals, and further to engaging conversations with chatbots (Schneiderman and Plaisant, 2004). Agassi and Weizenbaum (1976) extensively reflected on how humans adjust their behaviours based on their expectations of mechanised communicative partners. Nass and Moon (2000) as well as Reeves and Nass (1996) detail the Computers Are Social Actors (CASA) paradigm, which supports arguments for the integration of social elements to our responses to computers as a progressive approach to developing new communicative technologies. Additionally, Gambino et al. (2020) presents the human tendencies to anthropomorphise machines in instances of human-machine communication. Advancements in NLP and LLMs have arguably blurred the lines between human-human and human-machine communication in HMC studies (Weil, 2016). These new capabilities have enabled technology to simulate communicative agents more effectively, creating an illusion of sentience through natural language use that represented a "personified thing" (Etzrodt & Engesser, 2021, p. 73). Therefore, the act of writing prompts is framed as a novel mode of communication for HMC studies, wherein boundaries are dissipated between traditional understandings of communication with new technologic conceptions.

Prompt engineering involves crafting specific inputs to guide the model's output towards producing accurate, relevant, and contextually appropriate responses. Effective prompting requires a deep understanding of how these models interpret and generate text based on the given input, as well as a clear and intentional expression or request from the human user (Korzynski et al., 2023). By strategically designing prompts with natural language, users can elicit detailed explanations, creative content, and precise answers to complex questions (Knoth, 2024). Prompting engineering is, therefore, a critical technique for utilising this technology to its potential (Giray, 2023).

The concept of prompt engineering has established a significant niche within pedagogically oriented literature. This area is increasingly recognised as a core aspect for creating new educational strategies and practices around AI literacy. Prompting's pedagogical value can fundamentally be understood as a form of inquiry learning. Sharples et al. (2019) refers to inquiry learning as a pedagogical process whereby learners establish their own objectives, manage their learning schedule and pace independently, and decide when they have met their personal goals. By framing questions or problems, it engages users in a problem-based approach where the inherent curiosity drives the learning process (Dewey, 1938). This mirrors a form of cognitive scaffolding (Quintana et al., 2004), helping to manage tasks and enhance understanding while promoting student self-expression and reflection. Due to the similarities between the act of writing prompts and pedagogical inquiry, prompt engineering is often regarded as a valuable new practice, with a large academic voice spanning various discourses supporting its integration into education (Xie, 2023) (Herdliska and Zhai, 2023).

Literature focused on the pedagogy of engineering institutions have often encouraged the incorporation of prompt-related practices within higher education. Denny et al. (2024) views prompting as a new skill for constructing effective prompts for code-generating models. They introduce a programming exercise called 'Prompt Problems', where students learn to craft prompts that generate successful code solutions from LLMs. This new skill mirrors a more traditional practice within the computer science discourse of 'rubber ducky debugging', whereby one articulates their thought process and reasoning about code to an inanimate object, typically a rubber duck. This technique leverages the cognitive benefits of verbalising and structuring problems, which can lead to increased clarity and self-reflection, much like prompt engineering. Utilising this method capitalises on the pedagogical principle that teaching or explaining a concept can reinforce understanding and uncover hidden issues, making it a valuable tool for enhancing debugging skills and computational thinking.

Educational literature on the benefits of engaging with prompt engineering within higher education acknowledges positive potentials of integrating LLM technology into pedagogical practices, while also highlighting critical points and concerns from a more cautious perspective. Jowarder (2023), focusing on a group of social science university students, found that awareness, adoption, and perceived usefulness of ChatGPT significantly influenced its adoption. ChatGPT was described as having a positive impact on students' academic performance by assisting in understanding difficult concepts and providing relevant study materials. However, their findings also revealed that several students were overly reliant on ChatGPT for academic purposes, neglecting other external scholarly resources, which could impede critical thinking and independent learning in the long term. Furthermore, Cain (2024) suggests that effective prompt engineering practices, encompassing content knowledge, critical thinking, and iterative design underscore the transformative potential of LLMs in revolutionising education. However, to unlock these potential benefits and transform them into tangible realities, engagement among all stakeholders—educators, students, developers, and policymakers—is essential. This illustrates the evolving dynamics and expanding influence of the tech sector within higher education institutions, emphasising the critical need for collaboration between educators and technology developers to align values within educational technology. Walter (2024) demonstrates that LLMs hold significant promise in

enhancing inclusivity and accessibility within learning environments by supporting students with special needs, as well as equipping students with the necessary competencies of AI literacy, prompt engineering and critical thinking skills for a technology-driven future. However, they also address the pressing concerns regarding the preparedness of educators in this rapidly evolving AI landscape, as well as the ethical issues related to security, privacy, and equitable access to these tools to prevent widening educational disparities. Overall, whilst both perspectives from engineering and educational pedagogy collectively indicate that the cognitive processes involved in prompting can yield positive outcomes in an academic setting, there remains more to be understood about the responsible integration of these tools to ensure these benefits whilst limiting the harms.

Conceptualising Students' Present Methods of Engagement with LLMs

Academics have rapidly developed models, frameworks, and guidelines for prompt engineering. There is a plethora of literature which offers insights into how students ought to use LLMs. These frameworks are typically presented as guidelines to optimise AI interactions, emphasising their integration into educational contexts. Gao's (2023) discusses 'prompt hacking,' highlighting strategies to circumvent LLM restrictions and enhance performance. Techniques include 'Think step by step,''Role prompting,' 'Chain of Thought' and 'Few-Shot learning'. Lo's (2023) CLEAR model (Concise, Logical, Explicit, Adaptive, and Reflective) takes a more structured approach to prompt engineering. It emphasises the importance of understanding the technical aspects which influence the LLM's behaviour and output quality. Korzynski et al.'s (2023) framework for prompt engineering includes strategies such as articulating and refining instructions, tracking token length and offering feedback to the model. Further literature from technical fields frequently emphasises the value of LLMs by detailing strategies for prompt engineering, aimed at automating cognitive tasks to maximise the effectiveness of the technology (Kojima et al., 2023) (Logan IV et al., 2021) (Wei et al., 2022). These guidelines typically originate from technical backgrounds rather than educational ones, with AI-optimist perspectives that advocate for the rapid and widespread integration of AI into educational settings. This literature provides insight into the potential of LLM systems to assist students in higher education, without reflecting on the bottom-up nature of students' adoption of LLMs and their present engagement habits. There remains a critical need for educational literature to examine the present methods of engagement that higher education students are employing with LLMs in order to develop a comprehensive understanding of how institutions can effectively respond to the influx of LLM tools in education.

This research aims to address the gaps identified in the usage of LLMs within higher education more directly. Questions on what values and affordances students presently derived from this technology have relied on self-reported data derived from interviews, questionnaires, and surveys to gauge student perceptions and attitudes (Upadhyay et al., 2024) (Bernabei et al., 2023) (Chan and Hu,

2023). These studies show that LLMs act as major disruptors in higher education, promoting a paradigm shift towards learner-centred methodologies, enhancing comprehension and critical engagement with content, and are generally viewed positively in the context of teaching and learning. Although valuable for understanding students' views, methods which rely on self-reports are susceptible to biases like social desirability and recall inaccuracies, potentially skewing the data. Moreover, these studies fail to provide concrete insights into the specific approaches students take in interacting with the technology, thus presenting more of a descriptive recount of LLM effects in higher education rather than a probing analysis.

Existing research explores the affordances and applications of technology from both technical perspectives and educational viewpoints, including studies on prompting. Despite this, there is a discernible lack of studies focusing on prompts within educational literature, which could provide crucial insights into the actual adoption and utilisation of these technologies in practice within higher education. To overcome these limitations, this study will adopt a more direct approach by collecting and analysing prompts which students have written during their academic work processes. This approach aims to provide an explicit awareness of how students interact with LLMs, thereby offering a more granular and contextualised understanding of the value of LLMs as a technological affordance for higher education students. Collecting and examining these prompts allows for an in-depth analysis of how students construct their queries, the types of assistance they seek, and the effectiveness of their communication with the LLMs. This approach offers several advantages: it provides concrete examples of user behaviour, reveals patterns and trends in prompting techniques, and uncovers the nuanced ways in which students engage with the technology. Unlike self-reports or interviews, which can be influenced by recall bias or social desirability bias, the analysis of raw prompts delivers direct insights into the actual use cases and real-time problem-solving strategies employed by students. By identifying prompts as a channel of human-machine communications, this method addresses research gaps within HMC studies, particularly those concerning emerging areas of interest related to new forms of communication with AI subjects. Importantly, this research adopts a reactive rather than a proactive stance towards technological development; it is designed to assist educational institutions in responding to the integration of new tools, rather than in the development of those tools. This, in turn, will better equip educational institutions to manage the disruptive impact of these technologies effectively.

Research Questions

The primary objective of this research is to explore how higher education students engage with LLMs as part of their academic workflow. The study aims to address two main areas. First, it seeks to understand the nature of the prompts written by students. Specifically, it examines what exactly higher education students are writing in their prompts, the responses these prompts are intended to elicit from LLMs, and the purposes behind writing these prompts. Second, it investigates the impacts of LLMs on

students' workflows. This involves identifying the types of cognitive tasks that LLMs are completing for students and how understanding this method of engagement can inform the responses of higher education institutions.

Methodology

The Human-AI Communication (HAIC) Framework

In this research on understanding prompts as communication channels between students and LLMs, this paper draws upon HMC studies to provide a theoretical framework for analysing the communicative processes involved between students and LLMs in higher education settings. HMC studies have been utilised in educational research to examine various technological applications. Shang et al. (2022) applied HMC to analyse web interfaces for instructional purposes, while Edwards & Edwards (2018) explored the pedagogical impact of mobile technologies, such as phones and laptops, within classroom settings. Subsequently, a number of HMC scholars are promoting a deeper investigation into the more advanced and interactive AI technologies, focusing on human interactions with these systems and their broader societal impacts (Gunkel, 2012) (Guzman, 2018) (Peter & Küehne, 2018). Guzman and Lewis (2020) discuss the evolution of technology from a tool mediating human communication to an active participant in communication. They propose a novel framework specifically designed to understand human-AI communications (HAIC), distinguishing it from existing communication frameworks that focus on human-to-human communication. Their HAIC framework introduces three key dimensions for communication specifically with newer AI subjects.

Firstly, the **functional dimension** focuses on how users leverage the benefits of the technology to achieve their goals within their communications. This includes understanding how the context of communication, the user intention as well as the design and capabilities of the technology interact with each other to form a functional dynamic for the instance of communication to unfold. This dimension posits that each instance of user communication carries an inherent intention or goal, situated within a specific context. Users then evaluate the technological capabilities of their AI tools. These three elements—intent, context, and technological capability—jointly influence the formation of the communicative content, specifically the prompts in this scenario. For this paper's dataset, this dimension is the most relevant, as it entails making informed assumptions from the prompt data about the

objectives and contexts that students work with, as well as evaluating how the technological capabilities of LLMs are leveraged by the instructions or requests within the prompts. Examining the prompts students wrote can shed light on their intent and contextual factors behind the instances of LLM usage, offering deeper insights into the interplay between these factors and the values provided by the LLM. Following these principle foci, this analysis will attain insights towards theoretical groundings of prompts as a channel for understanding the affordances that arise from student communications with LLMs.

Second, the **metaphysical dimension** investigates the nature and existence of AI as communicative subjects, as well as the unique aspects of communication that occur between humans and AI which distinguish them from human-to-human communication. It probes the roles that AI assumes in these exchanges, underscoring the inherently one-sided nature of such interactions, where the human initiates communication for a specific purpose without any reciprocal benefit to the AI. The metaphysical framework builds on the functional dimension's insights into technology design by examining the broader context of the dynamics and relationships between the student and the AI as communicative entities. These analyses offer critical insights into the students' enacted agencies within these interactions.

Lastly, the **relational dimension** investigates how individuals perceive and develop social characteristics within their communications AI technologies. It explores the social roles that AI assumes and how these roles affect human perceptions and interactions, as well as how human communications with AI may incorporate elements typical of social interactions found in normal human-to-human communications. Prompts may contain instances of communication that signal social or interpersonal dynamics, thereby extending this analysis of LLMs to include their implications within social pedagogies. Baker et al. (2023) examines questions of how students and teachers relate to AI tools through how they operationalise culturally specific emotional concepts to imitate social agents within their functional design. Furthermore, Lomas et al. (2022) analyses the significance of resonance between users and AI as an effective design strategy. According to Polyportis and Pahos (2024), factors such as anthropomorphic qualities, design novelty, and user trust correlate positively with student attitudes towards ChatGPT and drive students' adoption of these AI tools. While the metaphysical dimension of HAIC provokes consideration of the unique nature of interactions between humans and non-autonomous machines—emphasising the distinctively one-sided nature of such communications—the relational dimension prompts us to examine how these interactions mirror conventional social communication. By examining prompts through this lens, this study aims to elucidate their role in social engagements with knowledge acquisition and learning objectives, thus framing these interactions as pedagogical engagements with AI technologies.

A significant limitation of Guzman and Lewis's (2020) HAIC framework is that it lacks clarity and precision, given its broad application across various contexts, with higher education being just one example. While the HAIC framework broadly considers human-agent interaction, it does not specifically account for how students in a university setting might use LLMs to enhance their learning experiences, manage their academic workload, or develop critical thinking skills. This study aims to build upon and clarify the framework by drawing on theoretical dimensions of pedagogical engagement from literature

on student engagement. This refined framework can help identify best practices, potential pitfalls, and areas for further research, ultimately contributing to a more precise and actionable understanding of student-LLM interaction in educational context.

Theoretical Dimensions of Student Engagement

While Guzman and Lewis's (2020) HAIC framework offer insights on what prompts, as a mode of communication, reveal about students' usage of LLMs, this study ultimately seeks to understand the effects of LLMs on students' approaches to their academic work amidst their increasing adoption in higher education. Student engagement theory is crucial to this study as this engagement is known to be adaptable and responsive to shifts in educational practices, making it a key factor to investigate amidst changing pedagogical environments (Appleton et al., 2008). Moreover, Bond et al.'s (2020) mapping of student engagement theory onto educational technologies further underscores the relevance of these dimensions in navigating the challenges posed by rising digital technologies in education. Therefore, educational theories of student engagement can assist in framing students' prompts for LLMs within a broader pedagogical process, revealing insights into how educational institutions can respond to their rising relevance.

In the context of LLMs in higher education, this paper refers to the established literature on student engagement that categorises engagement into three key dimensions which align with the HAIC framework. These include the **cognitive, agentic** and **social dimensions**. The cognitive component examines the intellectual engagement, which involves the depth of processing and understanding of the material. Fredrick et al.'s (2004) cognitive dimension of student engagement emphasises self-regulated learning, focusing on observable, purposeful behaviour that demonstrates operational reasoning. This aligns with the functional dimension, as both necessitate an examination of students' intent and their utilisation of technological capabilities to strategically mobilise this intent. Reeve's (2012) concept of agentic engagement extends this framework by considering how students take active control of their learning processes, making choices that influence their educational journey. This heightened sense of agency is linked to deeper, more meaningful learning outcomes, including the internalisation of knowledge and the development of a robust conceptual understanding (Bandura, 2006). This emphasises a focus on the ways in which students actively exert their agency during educational interactions, consistent with the focus on human agencies within the metaphysical dimension of HAIC. Lastly, social engagement, which mirrors the relational dimension of HAIC, examines how students interact with peers and instructors, emphasising the communal and communicative aspects of the learning environment (Fredricks et al., 2016). A significant body of research underscores the social foundations of knowledge and its acquisition (Jarvis, 2012), highlighting the importance of social goals in learning regulation. Donati (2010) posits that social relations manifest as emergent realities among

individuals, groups, and institutions engaging as social actors, establishing the accountability of their actions within their educational network and situation as well as informing the reflectivity of the subjects involved (Kahn et al., 2017). These three dimensions, thus, provide additional theoretical grounding for analysing the pedagogical implications of prompting practices within university students.

A prevalent challenge within student engagement literature is the broad definition of engagement, leading to considerable variability in how it is conceptualised and measured across studies. For instance, what one researcher defines as behavioural engagement may be seen by another as cognitive engagement (Christenson, Reschly, & Wylie, 2012). This broad definition not only increases overlap with other motivational and cognitive constructs but also dilutes the distinct contributions of engagement studies (Fredricks et al., 2004) (Eccles & Wang, 2012). Recognising the need for greater definitional clarity, this study aims to articulate a clear position within this body of literature, focusing specifically on the cognitive, agentic and social dimensions of students' momentary interaction with LLMs within their academic work in higher education. This approach, therefore, narrows its scope to the pedagogical engagement of self-driven student interactions with LLMs as strategic tools for achieving academic goals.

This research aims to utilise dimensions of student engagement alongside the HAIC framework, synthesising it with relevant theoretical models within this research context of LLMs in higher education to provide strong theoretical footing for this analysis. By utilising both these frameworks in an integrated manner, this research is able to interpret student affordances with new LLM technologies from the prompt data whilst also offering insights into the pedagogical implications of the rising level of student engagement with LLMs within the context of higher education. Furthermore, by exploring potential overlaps and interactions between the dimensions of each framework, a more robust method of analysing LLMs as digital interlocutors is conceived, enhancing our understanding of the pedagogical implications of students' prompts in higher education.

Research Design

To analyse prompts, this research employed questionnaires as the primary method for collecting prompt text from higher education students. These questionnaires also gathered contextual information about the students, including demographic details and academic background, which informed the analysis of the prompts. This approach enabled a comprehensive examination of the data, ensuring that the research questions are effectively addressed.

Recruitment of Participants

Given the recent increase in higher education students adopting LLM tools for academic work, and that LLM technology has become widely available for over a year at the time of this study, this research focused on the specific participant group of university students in the United Kingdom. It

employed a purposive sampling method to select participants, ensuring that all individuals were university students. Recruitment methods included snowball sampling, leveraging word of mouth and social media messaging within personal networks. Students were recruited across the University of Oxford, University College London, Imperial College London amongst others. This approach, while efficient and broad, inherently carried a sampling bias as it primarily involves participants from the researcher's existing network. Despite this limitation, the method is justified by the high usage rates of platforms like WhatsApp and Facebook among the target demographic, ensuring ease of communication, file sharing, and facilitating informed and voluntary participation.

The validity of findings was reinforced by the targeted sampling method, which allowed detailed and context-specific data pertinent to these research questions to be gathered. By focusing on university students, this paper was able to analyse the interactions with LLMs in an environment where such technologies are directly applicable and widely used. The inclusion of students from different academic fields and levels of study enhances the internal validity, as it ensures that the findings are reflective of a broad range of student experiences and academic requirements. The purposive sampling method, while effective for in-depth analysis within a specific context, inherently restricted the extent to which these results can be applied to non-university populations. The diversity within the sample offered a robust foundation for understanding LLM impacts in higher education, potentially informing similar studies across other educational settings.

Questionnaire Design

The questionnaire, created using Microsoft Forms, collected both demographic data and detailed information about participants' engagement with LLMs.

1. Demographic Information:

Participants provided their age, gender, and academic background, including both their past degrees and current studies. This information presented essential context and structure for analysing the interactions between human users and LLMs. Age and gender offered foundational demographic profiling of participants, while academic background played a critical role in understanding student intent by allowing the knowledge base and specific objectives students may have within their academic work to be inferred. This inference of intent and context behind instances of communication was a primary focus of this analysis within HAIC’s functional dimension and the cognitive dimensions of student engagement. This comprehensive profiling supported a nuanced exploration of how LLMs are utilised in educational contexts, enhancing the validity and depth of the research findings.

2. Prompt Sharing:

Participants were asked to share the prompts they have written for LLMs related to their academic work through two methods. The first method of link sharing leveraged a feature offered by most popular LLMs that generated a shareable link for conversations. Participants could input this link into the response boxes, allowing for the opening of a transcript of the entire conversation exchange between the user and the LLM.

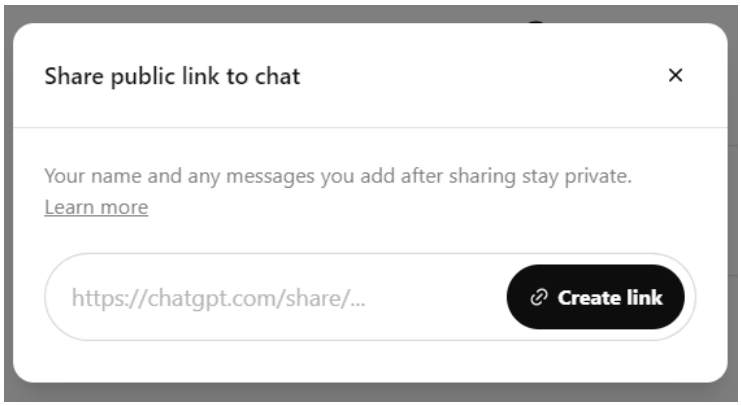

Figure 1: The Share Link function of OpenAI's ChatGPT.

This method was often the easiest and most straightforward way to share conversations in their entirety. The second method, manual pasting, allowed participants to manually paste selected prompts from their LLM's history into the response box.

There were different benefits and drawbacks to each method. Link sharing allowed participants to share their data through whole conversations. In contrast to individual prompts, which represent specific inputs or queries presented to the LLM, a conversation refers to the interactive and sequential exchange of text between a user and the LLM. This process involves multiple turns, with the user inputting text and the LLM generating responses, creating a dynamic and continuous flow of information (Bursztyn et al., 2021). Each turn builds upon previous exchanges, allowing for a more nuanced and context-aware interaction. Not only did link sharing allow more prompts per response to be gathered, it also revealed insights into the conversational nature of the interaction and provided a holistic approach to understanding each prompt within its context. Conversely, manual pasting involved sharing data prompt by prompt rather than whole conversations. Although more time-consuming, this manual method ensured that all shared data is relevant and focused on academic work, thereby respecting the participants' privacy while maintaining the study's focus. Ultimately, these two methods provided a comprehensive and flexible approach to collecting valuable data for understanding student interactions with LLMs.

Code Development and Data Analysis

The coding of prompts gathered by the questionnaire were guided by Guzman and Lewis's (2020) HAIC framework as well as aforementioned dimensions of student engagement (Fredricks et al., 2004) (Reeve, 2012) (Fredricks et al., 2016). Inspired by the previously mentioned literature on potential purposes for LLM tools to aid in cognitive tasks (Zhang et al., 2023) (Jiang et al., 2023) (Suh et al., 2023), as well as Bond et al's (2020) mapping of student engagement dimensions onto applications of educational technology in higher education, this research identified codes within the data by relating prompts' intention to the context of higher education academia. It was ensured that participants were exclusively higher education students and restricted prompt submissions to those written for academic assistance.

To effectively analyse student interactions with AI in educational settings, specific questions aligned with recognised HAIC dimensions were employed. These included: "What is this prompt aiming to achieve?" and "What value has this prompt derived from the technology's design?", which explored the functional and cognitive dimensions, clarifying the practical and intellectual impacts of AI prompts. Additionally questions like: "Does this prompt enable the student's agency?" assessed the agentic involvement, focusing on the roles of students' autonomy within their academic engagement with LLMs. Finally, social layers were explored through questions such as: "Does the prompt show signs of student emotional states?," and: "Does this prompt mimic human-human conversation in any way?", which assisted in examining the relational and social dynamics of students' communications with LLMs. Together, these strategic questions guided the systematic analysis of data, providing insights into the complex aspects of student communication with LLMs in higher education.

The analysis of data employed multiple techniques to extract meaningful insights into the rising student adoption of LLMs in higher education. Thematic analysis was used to develop major themes that describe commonalities and differences in prompting behaviours. This thematic analysis is aligned with principles of 'experiential' research, which seeks to interpret participants' thoughts, feelings, and actions (Clarke and Braun, 2017). This approach provides a deeper understanding of students' subjective experiences within their interactions with LLMs, thus capturing the necessary contextual cues for analysing the prompts as instances of HAIC. Additionally, by recognising the recursive process inherent in thematic analysis (Castleberry and Nolan, 2018), themes emerged through multiple iterations of data analysis. Initial codes were organised into larger categories fitting certain themes or trends based on the linguistic content and underlying sentiments of the prompts. This qualitative approach enabled a nuanced understanding of the distribution of students prompts as they interact with AI as part of their academic workflow. Furthermore, statistical analysis was employed to identify correlations and significant differences between groups. By scrutinising code distribution, the frequency of specific modes of engagement within prompts was made clear. This quantitative approach complemented the thematic analysis by providing empirical evidence of prompting behaviours. Guided by the aforementioned coding question, the analysis aimed to provide a comprehensive view of how prompts serve as mode of communication between students and LLMs in higher education.

Limitations and Corresponding Adjustments

There are several limitations inherent in the discussed methods that will be addressed. Firstly, is the variability in the volume of prompts each participant submitted. Whilst there was a minimum submission of six responses on the Prompt Sharing section of the questionnaire, the final number of prompts per participant varied widely, making direct comparisons across users challenging. Participants who contributed a large number of prompts may disproportionately influence the findings, overshadowing the contributions of those who provide fewer prompts and overrepresenting the behaviours and attitudes of a subset of participants, skewing the final results. To mitigate this limitation, the analysis focused not only on the total number of prompts within specific categories but also on the diversity of participants contributing to these categories. This dual approach enabled a deeper understanding of both the frequency of particular types of prompts and the distribution of participant engagement. By evaluating the number of unique participants alongside prompt frequency, a more balanced representation of behaviours and attitudes across the university student body was ensured.

In the process of coding the prompts, numerous assumptions had to be drawn, such as assigning students' intention and identifying parts of the prompt that were pasted from external sources. While the context of higher education and the data provided by each participant regarding their academic background informed these assumptions, they remain assumptions nonetheless. This reliance on assumptions introduced a potential level of inaccuracy and personal bias into the analysis, which must be acknowledged when interpreting the findings.

Ethical Considerations

Ethical considerations were rigorously adhered to in this research to ensure participant privacy and data integrity. Confidentiality was maintained by keeping all personal data and prompts unpublished unless explicit consent is obtained from participants. The research also acknowledges the contested role of AI in education, aiming to integrate these insights ethically to enhance educational practices. These ethical protocols extend to reflecting on the broader implications of AI in education, ensuring that the research contributes to the development of responsible and beneficial AI use in academic settings. Approval from the University of Oxford CUREC Board was also granted.

Findings and Discussion

After completing the collection, coding, organisation, and analysis of data, the findings and subsequent discussions will now be presented. The data explicitly addresses questions on what exactly university student prompts consist of by directly collecting the prompts which students have written themselves during their academic work. The semantic coding and organisation of these prompts effectively addresses questions regarding the methods of engagement that students were employing with LLMs. This section will present a systematic review of the thematic groupings of prompts, organised from the most to the least frequent. Initially, the significance of these thematic groupings and the affordances they provide to students will be explained with examples to elucidate their nature and implications for academic work in higher education. After the presentation of each major finding, they will then be analysed within the relevant HAIC and student engagement frameworks. This chapter will conclude with a table of engagement methods, detailing the number of prompts within each and the number of unique participants utilising each affordance or subcategory.

In this analysis, the primary findings were elucidated by applying Guzman and Lewis's (2020) HAIC framework, which enables a holistic and nuanced understanding of the prompts identified in the data. This encompasses the functional, metaphysical and relational dimensions of communications between humans and AI technologies. By leveraging the dimensions of the HAIC model, the underlying features of these prompts are discerned, such as user intentions, contextual objectives, technologic strategies, agentic engagements and social connections. The analysis will integrate dimensions of student engagement frameworks by drawing on the pedagogical implications from the same properties, ensuring that these dimensions are used in an integrative manner. This approach will enable the analysis of the resultant affordances and synthesise the pedagogical implications and educational insights of the prompts. Utilising solely the HAIC framework or the student engagement framework would be insufficient; however, integrating both frameworks derives effective insights into how higher education institutions can address the increasing adoption of LLMs among student populations.

1. Linguistic Manipulation

Linguistic manipulation broadly describes a method of engagement with LLMs to recreate or reshape text in certain manners, as well as the capability to carry certain sentiments within one text to another and reconstruct it with new language. This strategy relates to the NLP capabilities of LLMs, as it’s dependent on embeddings and vectors to construct meaning within linguistic symbols (Mikolov et al., 2013). Results show that a significant amount of student prompts centred on a few certain interrelated use cases. These consist of three: prompts which use the LLM as a thesaurus, prompts to reword input text and prompts which connect complex topics to one another. In this study, the most common application of prompts was for linguistic manipulation, as evidenced by 360 out of 896 (40%) prompts being employed for this purpose. Additionally, 22 out of 23 (95%) participants utilised this use case in their submitted data.

1.1 LLMs as Thesaurus

Within the context of participants in this study, LLMs have been utilised as advanced thesauri to support students' academic efforts in higher education. A common approach involved traditional practice with thesauri, where students would input a single term to receive alternative words with similar meanings. Out of 896 prompts collected, 72 (approximately 8%) were specifically used for finding synonyms.

"attitudes synonym"

"synonyms for categories"

Beyond this standard use case, students sought synonyms for longer phrases and complex concepts. This leveraged the model's constructions of semantics and context, which often represented abstract space between words rather than encapsulating the individual and distinct words themselves. This allows for the LLM to interpret multiple interrelated words, which often emerge as phrases, and re-constructed it as singular words or terms. Such prompts constituted a significant portion of the synonym-related queries, with 38 out of 72 (52%) focusing on converting phrases or terms into single words.

*"what is the word in economics to refer to **effects that were not the primary intention**"*

*"what do you call it when **the bad influences is coming from the outside**"*

*"'**on the other hand**' one word synonyms"*

In effect, this approach is not entirely novel, as early internet resources like OneLook [https://onelook.com/] have long provided users with the ability to find synonyms and definitions for extended phrases. However, this study's findings show that LLMs are increasingly popularising this capability among contemporary students, enhancing the frequency of its use in academic contexts.

Another strategy involved seeking context-sensitive synonyms. Students provided surrounding words of the final outcome sentences to ensure that the synonyms generated were contextually appropriate. This method relies on the LLM's capacity to understand the broader context, enabling it to deliver words that integrate seamlessly into the given text.

"what word can I use instead of service: the school prioritised instilling a sense of security among the students as part of its service"

“for this sentence "Secondly, the narrowing of the curriculum represents another outcome promoted by PISA." give me another word instead of outcome that fits better”

These examples indicate how students were employing the semantic and contextual capabilities of LLMs to find precise and contextually appropriate terms, reflecting a common category of practical use cases of LLMs for students in higher education.

1.2 LLMs to reword Input Text

Participants frequently utilised LLMs to rewrite text, leveraging the models' ability to convey the semantic and contextual information of the input in a different linguistic form. Unlike the thesaurus function, which is limited to single words or terms, these prompts sought outputs of varying lengths. Out of 896 prompts, 124 (13.8%) involved requests for text rewriting. Thematic coding segmented these prompts into rewriting in distinct tones or manners. 25 out of 124 (20%) specified rewriting the text in an "academic," "professional," or "smart" manner.

*“rephrase this **academically**: By increasing access to ART, PEPFAR not only protected the workforce from having to leave work due to immunocompromised diseases, but also by creating employment opportunities in the healthcare sector.”*

*“Please make this more **professional**, with actual sources - thanks[...]”*

*“Expand this **smartly**: one film I decided to look into was the film "Isle of Dogs" because of its Japanese setting. One scene that inspired me a lot was the cooking kitchen scene. I wanted to make something textured like wood."*

These requests illustrate the LLMs' ability to interpret and replicate specific tones, adapting the language to meet the stylistic and formal requirements of different contexts. This capability is particularly valuable for students who need to tailor their writing to various academic or professional standards, ensuring that their work is appropriately formal and sophisticated. Another segment, comprising 24 prompts, requested the text to be rewritten in a "concise," "clear," or "coherent" manner, allowing users to control the length and clarity of their responses—an aspect particularly useful for students aiming to condense the length of their writing or express themselves more acutely.

*“make this sound more **concise**: [...]”*

*“could you make it sound a bit more **coherent** : [...]”*

*“make this **clear** and academic: [...]”*

The majority of the prompts in this category (51.6% simply asked for a paraphrase of the text.

“Rephrase this [...]”

These examples illustrate how students were applying the advanced semantic and contextual capabilities of LLMs to enhance their academic writing by rewriting text to meet various stylistic and clarity requirements.

1.3 Writing from Input Data

Students were also able to reshape texts using LLMs by employing few-shot learning techniques (Gao, 2023). Specifically, they crafted prompts that included initial text, or input data, as a starting point, thereby guiding the model to generate additional coherent text in continuation of the provided excerpts.

“Based on this excerpt, write a short paragraph on criticisms and limitations of PEPFAR: [input text]”

Prompts of this nature can be viewed as functionally similar to rewrite prompts. Both present the LLM with an original input text which needs to be represented, or rewritten, in a new way to express the same sentiments or meanings through newly generated text. Overall, students utilise LLMs for both writing and rewriting to proceed with their academic work, employing the models’ capabilities to generate and refine text in various contexts. This practice highlights how students were using LLMs to facilitate both the creation of original content and the improvement of existing material.

1.4 Connecting Concepts

This study’s data reveals another interesting strategy used by students: prompting LLMs to integrate specific topics or concepts into a broader body of text. These prompts, which carry a substantial semantic load, enable students to generate text which includes specific knowledge and contexts.

“answer it with regard to this article: [input text]”

“*write a summary on the usefulness of funerary evidence as a source for Roman society. Touch on its relevance in providing insight into socio-economic climate, attitudes towards gender, and role of religion in society.”*

In these examples, the student guided the LLM to include certain topics, ensuring that the generated response is not only relevant but also includes a specific context or detail. This approach allowed students to exert control over both the tone and the subject matter of their written work, effectively steering the direction of their arguments and discussions within their texts. This method highlights the value of LLMs in academic settings to automatically integrate and relate certain details, points and subjects within larger bodies of texts in their writing. It demonstrates the affordance of LLMs to incorporate relevant information and context, generating responses which are appropriately detailed within their desired contexts.

1.5 Understanding Input Text

Just as students utilised LLMs to translate the sentiments of their text into academic or professional language, the process was also reversed to decrypt text from academic or professional sources into more accessible and comprehensible language. Although a low number of prompts (5%) represented this category, these were spread across 16 unique participants (69%).

> *"[input text] summarise the above into key dot points please"*

In these examples, students demonstrated the transforming of dense material into more concise and straightforward summaries. Additionally, students posed targeted queries to extract specific information from texts, such as:

> *"how does this illustrate the role of local agencies as stakeholders in PEPFAR: [input text]"*

These prompts demonstrate how students direct the LLM to distil essential information from detailed texts, producing responses that meet their specific academic needs. This interaction not only simplifies the information but also tailors it to the students' inquiry, showcasing the capability of LLMs to facilitate understanding and engagement with complex knowledge through strategic linguistic manipulation.

Discussion of Linguistic manipulation

This analysis will employ the functional dimension of the HAIC framework in conjunction with the cognitive dimension of student engagement to gain insights into how students interact with LLMs in higher education through linguistic manipulation prompts. The functional dimension examines how user

intentions, context, and the capabilities of the technology shape human-AI communication. Meanwhile, the cognitive dimension of student engagement focuses on students' observable self-regulated strategies and operational reasoning. By integrating these two dimensions, the analysis will elucidate how students' self-regulated strategies and reasoning processes connect their intentions and context with the technological capabilities of LLMs.

Student's linguistic manipulation of text using LLMs evidently occurred across a wide variety of academic contexts. Whether selecting precise words or phrases or reworking entire sections of text, students exhibited clear intentions of producing academic or professional text. Their prompts often utilised LLMs' word embeddings as a technological capability, which map words to vectors in a multidimensional space where semantically similar words are closely positioned (Mikolov et al., 2013). Thesaurus prompts [theme 1.1] exemplify this capability by explicitly searching for similar words or phrases, though these prompts are typically short and reveal little about the cognitive strategies involved in student engagements with LLMs. While the practice of finding semantically similar words is not new, as evidenced by the existence of traditional thesauri, the analysis of prompts aimed at rewording input text [theme 1.2] provides deeper insights. These prompts indicate that students were actively evaluating their written work, identifying areas for improvement, and using LLMs to refine their language. In academic writing, operational reasoning is critical, as it involves organising thoughts, selecting effective vocabulary, and adhering to academic standards. This reasoning also entails applying logical thinking and problem-solving skills within the parameters of academic and professional language norms. Students demonstrate operational reasoning by considering how to phrase arguments, select the appropriate tone, and restructure sentences for clarity and impact. Through this iterative refinement process, students employ strategic and self-regulated approaches to enhance their academic writing.

These findings illustrate that linguistic manipulation, a benefit students gain from using LLMs in higher education, signifies a functional shift in the way students approach writing academic texts. Given that 91.3% of participants engaged in prompting for linguistic manipulation, and that 32.8% of all prompts collected in the dataset were utilised to manipulate the language of text, it is evident that this function represents a significant aspect of the value that students derive from using LLMs in higher education. Traditionally, students in higher education are expected to adhere to high standards of academic literacy, which involves using specific jargon and adopting appropriate tones for various tasks (Li, 2022). This change can particularly assist those who struggle with these standards, including non-native English speakers or students with learning disabilities, by simplifying complex explanations and language use (Murray, 2022). When writing these prompts for manipulating linguistic representation, students were focusing on conveying underlying sentiments rather than intricate linguistic forms. This enables them to express complex ideas more confidently and clearly without the added challenge of navigating unfamiliar academic language. LLMs can therefore serve as valuable tools in equalising educational opportunities for students with varying levels of proficiency in academic English, making higher education more accessible for all students, including those with learning disabilities and non-native English speakers.

Within the cognitive dimension of student engagement, this analysis demonstrates that using prompts to manipulate linguistic representation can be considered a useful pedagogical strategy. However, these strategies diverge significantly from traditional cognitive strategies like rehearsal and summarisation discussed in student engagement literature. By enabling students to transform simple or non-academic text into more precise or scholarly language through prompts, LLMs essentially shift the cognitive load from students to the technology. This shift is prominent within prompts which are used to convert cryptic academic texts into more digestible and comprehensible formats [theme 1.5]. Students predominantly engage with the simplified text without a direct scrutiny of the original cryptic versions, circumventing the cognitive exercise of decoding complex academic language and potentially limiting their opportunity to develop critical reading skills essential for academic growth. While cognitive shortcuts are evident in both the simplification of complex text and the conversion of simple text into more complex formats, this study's data does not conclusively demonstrate that students' cognitive processes are being supplanted by engagement with LLM technology. Specifically, the findings do not indicate that students were exclusively relying on these technologies for cognitive tasks. In reality, they may be using them in conjunction with traditional strategies. Rather, this data indicates that LLM technology offers students a new affordance, allowing them to write prompts instead of bearing the cognitive load associated with consuming or producing academic or professional text. Huang's (2023) report of widespread student adoption of LLMs alongside Newport's (2016) and Connaway et al. (2011) principles of convenience over content suggests that students may opt for the easier approach of prompting rather than undertaking the more demanding task of independently creating or decrypting text. Consequently, while linguistic manipulation engages operational and self-regulated strategies, it offers students a convenient alternative, potentially bypassing the critical cognitive processes essential for effective academic writing and reading. Promoting the increased use of these prompts could potentially diminish the essential cognitive engagement typically involved in mastering language skills. As students grow accustomed to the convenience of AI-assisted linguistic manipulation, they risk becoming less inclined to engage deeply with challenging materials or to exercise independent problem-solving skills (Long and Magerko, 2020). This trend could potentially diminish their ability to analyse and synthesise information without technological aid, a foundational component of scholarly competence and intellectual rigour.

Understanding the pedagogical advantages and disadvantages of students writing prompts as a form of cognitive engagement with AI can provide valuable insights for the responsible integration of LLM technologies into higher education contexts. As AI-assisted manipulation of language becomes increasingly common, it is imperative for educational institutions to address the potential risks of dependency. Historical scepticism towards technologies like calculators, which automate cognitive calculations, mirrors current concerns about LLMs taking over linguistic manipulations. During the introduction of calculators, Taylor and Nichols (1994) emphasised the continuing importance of mental arithmetic skills in developing a student's mathematical education. Similarly, Wang et al. (2024) advocate that to maximise the benefits of ChatGPT in comparable learning settings, students should master prompt engineering techniques and have a solid foundation in the knowledge required for their tasks. Drawing parallels to LLMs, the automation of text manipulation by these models suggests a similar

educational strategy is required. By encouraging students to independently manipulate text and engage in mastery learning exercises such as paraphrasing, peer reviews, summarisations, educators can foster a deeper mastery of academic language and linguistic structures. Furthermore, practising exercises based in real time, such as debating, can encourage a dynamic engagement with relevant linguistic skills, promoting the persuasive articulation of thoughts in real time with precise use of language. Integrating linguistic activities for mastery learning that reinforce the cognitive skills typically automated by LLMs will help mitigate dependency issues and enhance overall educational resilience of students in higher education.

2. Engaging with Corpus Data

The capability of LLMs to understand and generate natural language stems from the extensive corpus data from which they are trained. Corpus data consists of large collections of text that can include books, articles, and web content, providing a broad sample of language usage. Given the comprehensive nature of this data, it contains a wealth of information that students often seek to access for various academic efforts, highlighting another affordance of LLMs as a valuable informational resource. Accordingly, prompts designed to interact with the corpus data of LLMs represented a significant use case in this study. Data indicates that 245 out of 896 prompts (27.3%) submitted were of this type. These prompts generally took the form of direct questions, which varied widely in their level of complexity.

2.1 General Questions

General questions can help students navigate unfamiliar subjects, enabling students to get coherent generated responses to questions on demand. 59 of the 311 prompts (18.9%) within this category were coded as “general questions”, which were typically quick and more conversational. This helps students get certain details right in there writing:

“when was the Sen's theory published”

“how do I capitalise this heading: [...]”

However, the questions posed were predominantly technical in nature, being specific and frequently addressing advanced topics across various disciplines.

2.2 Technical Questions

These questions often involved detailed explorations of specialised topics and utilised jargon that could be perplexing to a non-expert audience.

> *“what is the definition of modernisation in a economic international development context“*

> *“what details of the feedstream would you need to include in a report about isolating IGF-1 from human blood”*

> *“what does the presence of gods on roman funerary art reveal about religion in roman society”*

> *“in the context of fluid dynamics, what is the difference between T-S and crossflow modes in boundary layers?”*

These questions engaged the corpus data in an active search for new information, utilising the LLM differently from linguistic manipulation prompts. Rather than relying on the model's capability to reshape text and linguistic representations, these prompts required the LLM to extract information from its extensive training dataset, which comprises online sources covering a wide range of technical topics. This approach reflects a distinct utilisation of the model, focused on information retrieval rather than text transformation. These prompts not only delved into the corpus data, but the use of natural language as an instructive medium also enabled students to specify particular issues within complex topics for troubleshooting.

> *“When I am trying to run a linear regression on spss and I am trying to add my dependent variables, sleep, anxiety, and depression into the dialog box, it wont let me add more than one dv. How do I fix this?“*

> *“I don't have a residual variable .... it's the sum variable above - how would it work this case”*

The real-time responses and conversational interface of large language models facilitate the posing of follow-up questions in a similar manner, allowing for an iterative process that focuses on precise information retrieval.

2.3 Using Corpus Data to Write

Participants demonstrated tendencies to instruct LLMs to generate text. Contrary to earlier prompts that requested text to be "written" based on input source text, these writing prompts rely on the corpus data of the LLM as the source of information.

“write a paragraph on how the hippodrome demonstrates the evolution of constantinople”

Although fundamentally similar to direct questions, these prompts are structured differently, and are instructive rather than inquisitive. This method leveraged the LLM’s ability to synthesise and present data in a coherent form, reflecting not just factual recall from the corpus data but also an understanding of context and relevance in relation to the prompt. Both types of interactions—direct questions and instructive prompts—utilise the model’s training to inform and construct content that is contextually appropriate and richly detailed.

2.4 Using Corpus Data for Quantitative Inquiry

While this study’s discussion around LLMs often centres on their language capabilities, students were also using these tools for quantitative tasks such as complex calculations and programming assistance. Whilst these requests were within a quantitative domain, LLMs were still able to provide value by tapping into their extensive corpus, which includes texts with numerical information, statistical analyses, and mathematical concepts. This expansion of use reflects a broader spectrum of LLM affordances, demonstrating their versatility and applicability across a range of academic disciplines. Within the sample population, students demonstrated that they were leveraging these tools for tasks that extend beyond traditional language processing, such as performing complex calculations and assisting with programming or coding challenges. Despite the even distribution of participants from STEM (52.2%) and humanities degrees (47.8%), the findings showed that this was a relatively uncommon occurrence, with only 49 out of 896 (5.4%) prompts indicating this affordance from 7 out of 23 (30%) unique participants.

2.4.1 Using Corpus Data to Calculate

One method students employed to leverage the quantitative affordances of LLMs was by requesting calculations. It is crucial to recognise that the students’ calculations facilitated by LLMs extend beyond simple arithmetic that might typically be handled by a calculator. These complex calculations often involved multiple layers of data and were not confined merely to numerical operations.

“Calculate inhibitor (Z uM) where 50 uL inhibitor concentration, BuChE 50 uL, DTNB & BuTCl 20 uL for total volume of 120uL”

“Show that the electric field component in the x direction is invariant under a lorentz boost in the x direction”

Such tasks require an understanding of both the numerical data and the scientific principles that govern these interactions, demonstrating the LLMs' capability to synthesise and apply multifaceted academic knowledge from its corpus data within specific contextual frameworks.

2.4.2 Using Corpus Data to Code

Another method involved requests for code to be written. This mainly included the editing of code, rather than writing code from scratch. Student’s used prompts as a way to express what they wanted in their code with natural language. This constituted the majority of requests of a quantitative nature, with 43 out of 49 (87%) of quantitative prompts being related to coding.

“I want my python code to while True: a = f.readline(-1) l.append(a) and if there is no more line to read break the loop”

“What about cumulative explained variance ratio? Just give me the code”

However, despite these uses, coding requests elicited a notably higher level of dissatisfaction among students compared to other types of prompts, often leading them to request that the LLM attempt the task again.

“Still get same mistake”

Despite the challenges in achieving consistent and reliable outcomes, such instances highlighted the practical affordances of LLMs in aiding students to refine and implement their academic coding projects.

2.5 Literature and Citing

Students seeking assistance with locating literature and integrating citations into their academic work also utilised LLMs for support. These prompts tapped into the LLM’s corpus data on citation methods, as well as its ability to search the live web for academic texts. Inquiries of this form typically involved searching for academic sources or requesting help with the proper citation of texts within their academic projects. Out of 896 prompts, 60 (6.7%) from 10 out of 23 (43.4%) unique participants were related to these tasks.

2.5.1 Source Searching

Prompts involving the search for sources leveraged the LLM's capability to scour the web for academic material relevant to the students' specified topics

> *"What are some sources that talk about PEPFAR being driven by economic interests of U.S pharmaceutical industry and to widen market access of general U.S goods and services"*

> *"Give me a literature list with papers on how school teachers do not have the time to teach global education disciplines to their students"*

These examples demonstrate how students could articulate specific academic inquiries with precision, seeking out targeted articles to incorporate into their work. However, it is crucial to note that many of these searches were not successful. Students often reported that the provided links were non-functional or that the retrieved literature did not meet their needs. This suggests that while source searching via LLMs was a pursued affordance, it may not always be effective. Despite these challenges, the data indicates that students were turning to LLMs for this purpose in higher education

2.5.2 Citation Assistance

In addition to sourcing references, students also utilised LLMs to assist with the actual citation process in their academic work. This assistance included direct requests for citing specific sources as well as inquiries about different citation styles to ensure their references were formatted correctly.

> *"Cite this document by referring to this link: [article link]"*

> *"What do I do in harvard reference if data in multiple of my paragraphs are from the same source"*

> *"How to report non-significant R-squared change in APA format"*

In these instances, similar errors and inconsistencies were observed in requests that required the LLM to open links or handle web browsing, often resulting in inaccurate or incomplete citations. Despite these challenges, students found value in their direct inquiries about citation practices, highlighting the affordances of LLMs in assisting with academic citations in higher education.

Discussion of Engaging with Corpus Data

By examining the questions within students' prompts, this study gains insights into the subject areas they are exploring and the specific informational requests they are making across various academic practices. This analysis addresses the context and intentions behind students' communications with the LLM, establishing a foundational basis for the functional dimension. Furthermore, examining the design features and capabilities of LLMs—particularly their training on an extensive corpus encompassing diverse web and academic sources—clarifies the technological capabilities that students leverage to fulfil their intentions. Utilising the cognitive dimension of student engagement alongside this analysis highlights the cognitive strategies employed to actualise intent through interaction with technological capabilities. Interactions which involve using natural language to pinpoint and retrieve specific information constitute self-regulated and inquiry-learning strategies (Sharples et al., 2019). These strategies were evident as students engaged in prompt engineering—formulating questions that reflect an understanding of LLM capabilities aligned with their academic objectives. This method proved particularly effective for technical inquiries, as students leveraged the corpus data to identify and address gaps in their knowledge actively. This approach demonstrates how they establish their own objectives and independently manage their learning schedules and pace within a problem-based framework. Moreover, even general inquiries contributed to this cognitive engagement by allowing students to identify their own knowledge deficits and engage in a more immediate and conversational style of interaction, thus promoting a deeper, iterative learning process. This conversational approach will be explored further in relation to the interpersonal and social engagement dimensions of these frameworks.

Although the corpus data of LLMs is a major feature that students' were utilising, academic bodies often warn of its inherent biases and embedded values that present challenges in educational settings. Zembylas (2023) introduces the concept of "algorithmic coloniality," highlighting how AI systems can reinforce colonial dynamics and power imbalances through the use of extensive datasets that predominantly represent the experiences and viewpoints of dominant groups. Algorithms which search navigate online data have been critiqued for reinforcing oppressive social dynamics (Noble, 2020), with decolonial scholars such as Mbembe (2017) arguing that these technologies signify a new phase of modernity that continues to influence racial structures in global society and extend long standing racial and colonial legacies. Pisica (2024) also details how the upwards trend of AIED in contexts like Romania demonstrates rapid digitization in educational environments that are not aligned with the dominant Western contexts from which these technologies originate and often exacerbates the lack of strategic vision in successfully integrating these technologies. This issue is particularly evident with LLM models like ChatGPT which primarily sources its data from the US and other English-speaking contexts. The propagation of Western ideals and the spread of inaccurate information can perpetuate Euro-centric ways of knowing and the values, as well as marginalise and obscure the knowledge systems of less powerful communities. The significant influence wielded by technology companies in the educational

sector is creating an imbalance, embedding Eurocentric values and principles derived from Western datasets onto a global user base. Although this study's findings does not directly address the impact of these limitations on students, it does highlight the growing relevance of this corpus data as a popular source for student information retrieval. Therefore, as students increasingly utilise corpus data over other sources, it is crucial to address the inherent issues within LLMs as sources of information.

Additionally, a significant limitation of LLMs as a source of information is their propensity for "hallucinations" Ivanov (2023). Operating on statistical reasoning, LLMs lack the capability to discern factual accuracy, often generating responses that are statistically plausible but factually incorrect. This becomes a critical issue when students, overly reliant on LLM responses, fail to recognise these inaccuracies, inadvertently incorporating erroneous information into their academic work. These biases and limitations, if not critically examined, can significantly impact the academic integrity and inclusivity of educational environments, risking the uncritical acceptance of data by students. Within this dataset, students demonstrate an awareness of these inaccuracies, which will be discussed later in the assessment of the metaphysical and agentic dimensions of student engagement with LLMs.

Higher education institutions can effectively tackle the challenges posed by the increasing reliance on corpus data as an informational resource by fostering AI literacy within their curricula. This approach involves engaging students in exercises that develop their ability to critically assess AI-generated responses, highlighting the need for cultural sensitivity and awareness of potential biases—key components in decolonial educational efforts. It is crucial for students to understand the nature and limitations of corpus data and critically assess their responses in light of the potential for hallucinations or Euro-centric biases. Educators within higher education should elucidate the underlying concerns with LLM corpus data and integrate discussions on the critical evaluation of AI-generated content into their curriculum. This echoes sentiments of scholars like Southworth et al. (2023), who advise for students evaluation of the quality, reliability and ethical considerations of AI generated responses as pillars of AI literacy within higher education curricula. By positioning LLMs as one of many data sources, rather than a universally accurate and reliable tool, students can be encouraged to be critical in their analysis of the responses they receive from LLMs, as well as explore multiple avenues for obtaining necessary information. Encouraging students to critically evaluate the validity of responses generated from corpus data not only helps them identify gaps in their knowledge but also guides them in finding accurate and reliable information to address these gaps.

3. Ideation

Another method of engagement students employed with LLMs in higher education was utilising them to assist with ideation. The sample of students frequently used prompts in ways that aimed to generate new ideas or provide starting points for creative or original thought. They assisted students by suggesting research topics, aiding in the structuring of lengthy texts, or facilitating the creation of ideas to inspire creative thinking. The analysis highlighted ideation as a significant category, with 97 out of the total 896 prompts (10.8%) focused on this function, and 19 out of 23 (82.6%) unique participants utilising this feature.
Ideation occurred primarily through two prompting methods, exploratory ideation and requests for feedback.

3.1 Exploratory Ideation

Although these prompts resemble general questions in form, they differed fundamentally in purpose and context. Rather than seeking specific answers, these prompts aimed to extract new ideas from the corpus data, facilitating brainstorming or the generation of original and creative concepts.

"I need some help formulating an essay on feminism"

"what are important section for my dissertation about:
An exploration of the procedure for diagnosing ADHD and the impact of late-stage diagnosis on young adults."

"what would be a good name for a physiologically relevant cell culture medium"

These prompts were commonly used in the early stages of academic work, particularly in helping to structure initial ideas when starting from a blank slate. The results demonstrate that students were utilising LLMs as tools to aid in brainstorming and cognitive tasks.

3.2 Evaluative Ideation

Evaluative Ideation was another method students use to extract novel ideas from LLMs by requesting feedback. These prompts typically included a piece of text originally composed by the student, accompanied by an instructive request for feedback on specific aspects of the text to facilitate improvement.

"give me suggestions on this paragraph: [input text]"

“ ‘High rates of psychological morbidity in university students are especially prominent in depression and anxiety' does this sentence make sense”

“rate this depth and response in letter grade: [input text]”

Feedback obtained from these prompts varied from general suggestions to specific inquiries about logical progression and the anticipated grade, reflecting the academic context of the work undertaken by students. These prompts directed the LLM to offer fresh insights into the submitted text, presenting students with new perspectives that can enhance their existing work. Unlike exploratory prompts, which were commonly employed in the initial stages of academic projects, these evaluative prompts were typically used towards the end of the process. These prompts reveal how students were utilising LLMs to assist in producing academic text that is comprehensive and not lacking in any essential elements or areas.

Discussion of Ideation

Ideation represents a type of engagement that, while leveraging the AI model's capabilities, does so less directly compared to previously discussed prompts. Within the functional dimension of the HAIC framework, examining how the design features of LLMs facilitate ideation reveals similarities to previous types of engagement. For instance, when students crafted prompts aimed at aiding ideation—such as

“what would be a good name for a physiologically relevant cell culture medium”

—they still fundamentally rely on the LLM's capabilities in NLP, linguistic manipulation, and the corpus data to generate a response corresponding to the precise subject and context. These tasks, whether generating essay ideas or brainstorming names, utilised the LLM’s ability to search its corpus for relevant topics and express them linguistically in precise output manners. Despite this, a critical aspect of HAICs functional framework is the understanding of how the prompt’s context and the students’ anticipated outcomes interact with the functional design elements of the technology, thus distinguishing ideation prompts from those focused solely on linguistic manipulation or drawing from the corpus data. Analysis of such prompts under this framework highlights that, although they utilise similar technological functionalities, the contextual application in ideation is distinct. The data demonstrated that students used ideation prompts to seek ideas and inspiration, reflecting a different type of cognitive engagement with the technology. This engagement differed from prompts that merely request text rewriting or seek direct answers from the corpus data. Ideation prompts encouraged students to think more abstractly and creatively, pushing them to formulate questions that stimulate the generation of new ideas rather than retrieving known information. This nuanced difference in application demonstrates LLMs’ abilities to not only retrieve and reformat information but also to foster creative and original thinking in students.

Thus, while ideation prompts employ the same foundational technologies as other types of engagement, their context, purpose and impact on student learning diverge.

The cognitive dimension of student engagement frameworks emphasises the self-regulatory strategies embedded within student activities. The data demonstrated how ideation prompts, exploratory ideation [theme 3.1] in particular, mark a distinct cognitive phase within a student's academic workflow, where they actively seek inspiration or initial ideas to begin their projects. Furthermore, evaluative ideation [theme 3.2] reflected essential SCL processes such as self-evaluation and peer-evaluation. Like prompts that engage with corpus data, ideation prompts serve as cognitive scaffolding, helping students identify knowledge gaps and define clear next steps in their academic workflow (Quintana et al., 2004). This scaffolding aids students in visualising and strategically mapping out their creative pathways, enhancing their ability to navigate through complex academic tasks. By facilitating this level of cognitive engagement, the use of ideation prompts constitutes a strategic application of cognitive and inquiry-based learning principles.

Despite these pedagogical implications, academics of AI cognition claim that it is fundamentally impossible for LLMs to generate truly original thoughts independently (Franceschelli and Musolesi, 2023), which makes reliance on these models for creative outputs seem somewhat counterintuitive. The underlying logic and reasoning capabilities of LLMs differ markedly from human cognition, challenging their ability to authentically contribute originality or creativity to a student's academic endeavours. Nevertheless, this data clearly demonstrates that students were continuing to seek out these technologies for creative inspiration in their academic work. These considerations imply that students' reliance on LLMs to generate creative value in their responses may undermine the pedagogical goals of fostering genuine creativity and critical thinking in educational settings. Furthermore, since ideation prompts depend on corpus data as a source of information, they inherit the same limitations associated with this data, including the potential for inaccurate or biassed responses. Although the dataset does not show the extent to which students utilised the output from ideation prompts, the embedded biases and values within these responses can still subtly influence their academic work, affecting the development of their independent critical faculties and potentially perpetuating harmful stereotypes. Moreover, issues with hallucinations within LLM outputs persist, necessitating critical evaluation by students of the responses provided by these models. This complex interplay between LLM capabilities and educational objectives highlights the need for careful integration of these technologies within pedagogical frameworks to truly enhance learning outcomes without compromising academic integrity.

Ideation prompts illustrate the cognitive strategies that can be facilitated through adoption of LLMs, despite significant inherent limitations. Cultivating AI literacy among students would enable them to more critically understand the nuanced issues associated with LLMs' corpus data and statistical reasoning, echoing a perspective from Walter (2024) which advocates for the development of critical mindsets to fully harness AI technologies in higher education. Furthermore, it is crucial to encourage students to engage with LLMs in a manner that enhances their original thinking and creative decision-making capabilities. LLMs can aid students in visualising creative pathways and assist with

constructions of arguments and brainstorming tasks, serving as AI tools with an assistive capacity rather than a primary one (Zdravkova, 2022). Students should cognitively engage with the text generated by LLMs as a starting point for student creativity, inspiring their own unique contributions rather than replacing them.

4. Controlling the LLM

Another prevalent method of engagement with LLMs tools was the ability to communicate with it in a way that specifically directs the output manner of the LLM.Prompts which controlled the LLM assumed a more directive role, focusing more on how the LLMs are utilised as tools rather than on the substantive academic task itself. Controlling the LLM in this context was categorised into two sub-codes: response tinkering, which involved making precise adjustments to the model's responses, and preparing the LLM, which set specific parameters for how the model should approach a task. Out of 896 total prompts, 126 (14%) were coded to be controlling the LLM in this sense, from 17 unique participants (73.9%).

4.1 Response Tinkering

Response tinkering typically occurred when students were dissatisfied with a previous response. These prompts specifically targeted errors or desired changes, focusing directly on the functionality of the LLM rather than its primary capabilities, such as accessing corpus data or utilising NLP skills. Examples illustrate that these prompts often concern the format, length, or specific nature of the response itself, indicating a direct interaction with the operational aspects of the LLM.

“I don't want you to rewrite the code i want you to debug my code which is import sys”

“Please condense this information in the structure for one paragraph”

“For the previous request, make sure the concentrations are present as well”

These prompts demonstrate the capability of students to refine and iterate on their responses effectively. This process highlights the value of the conversational nature of the model, allowing for dynamic adjustments and improvements in the interaction.

4.2 Preparing the LLM

Prompts which directly controlled the LLM also included those that prepare the LLM for a specific task. These prompts differred in that they were not crafted to elicit the desired output immediately, but served as a unique form of communication to establish a mutual understanding between the student and the LLM regarding the expected task.

> *“Ok chatgpt i need to write an evaluation on my project. Can you help me reword the text I'm about to send you?”*

> *“For all following messages, unless I state otherwise, I only require you to provide the hypothetical code I would need to write - you don't actually need to process anything”*

It is important to note that only three unique participants engaged with LLMs in this manner. The majority of users did not partake in this type of direct communication with the LLM within their submitted prompts.

Discussion of Controlling the LLM

Scrutiny of how students were engaging in communication with the LLM in an effort to control the LLM’s output parameters leads towards considerations of the metaphysical dimension of the HAIC framework. Whilst the functional dimension aims to elucidate the practical value that technology was able to provide human users, the metaphysical dimension homes in more on the roles behind the communicative agents. It examines the extent to which AI entities serve as genuine partners in authentic exchanges or if they merely function as extensions or echoes of human communication. This focus on agency highlights the relevance of the agentic dimension of student engagement, which investigates how students take a proactive role in their learning by providing input, stating preferences, and posing questions. This active participation is crucial as it extends beyond passive reactions to instructions and actively involves students in modifying and influencing the instructional process itself. Each prompt inherently reflects an aspect of student agency, manifesting the active decisions and efforts students make in composing and submitting these prompts. However, the analysis specifically targets prompts that control the LLM [theme 4]. These particular prompts more distinctly showcased student agency, as they placed students in a directive role where they autonomously and strategically defined certain aspects of the LLM’s response. This focus underscores the heightened roles of students’ agency within their engagement with LLMs in higher education.

Prompts which aim to control the LLM’s output adopted a more directive approach towards the LLM, rather than simply instructing or asking questions. These prompts engaged with the LLM more

explicitly as a communication partner, yet simultaneously underscore its role as a practical, assistive tool rather than a true interlocutor.

> "Ok chatgpt i need to write an evaluation on my project. Can you help me reword the text I'm about to send you?"

Although this prompt is functionally aimed at rewording text, the mode and purpose of communication did not seek to directly elicit a response. Such prompts indicate that students assumed a commanding role, directing the LLM towards producing specific outputs. This not only highlights the functional use of the LLM as a tool but also reflects the power dynamics inherent in these interactions, where the LLM is subservient to the human user's educational goals. Similarly, prompts that aimed to refine or adjust LLM responses also demonstrated a form of student agency through students' self-positioning in their interactions with the LLM [theme 4.1]. This study's findings indicated that these response-tinkering prompts generally arose from student dissatisfaction with initial outputs.

> *"For the previous request, make sure the concentrations are present as well"*

Building upon the functional dimension of the HAIC framework, which assesses the context of the interaction, as well as the metaphysical dimension, which examines the relational positions of the communicators, the effective influence of students' autonomy becomes evident. The contexts of these prompts within the wider conversation with the LLM showcased the students' capacity to critically evaluate and reject unsatisfactory answers, demonstrating intentional and deliberate engagement with the technology. This critical engagement indicates how students were actively shaping the output of the LLM to better meet their academic needs.

Agentic engagement, as defined within a classroom setting, is characterised by learners actively contributing to and shaping their instruction and learning outcomes (Reeve, 2012). Similarly, in the context of interactions with LLMs, students engaged pedagogically with these AI systems as communicative agents, without being confined to traditional classroom environments. Such engagements were pervasive across various themes, highlighting the students' autonomous and deliberate decision to integrate LLMs into their academic tasks. Prompts which controlled the LLM was the third largest category within the themes, reflecting the frequent exercising of student agency in their communications with the LLM. Interactions with LLMs typically showcased a constructive and iterative process where students not only generate text but also refine and adjust AI responses to better meet their academic needs. This process exemplified a level of critical engagement, indicating that interactions with LLMs are not merely transactional. Instead, they involved continuous cycles of modification to achieve outputs that more closely align with the students' objectives and expectations. This iterative engagement model extends the understanding of prompts as student interactions with LLMs, suggesting that these are not isolated cognitive transactions. Instead, students were actively involved in ongoing evaluations and modifications, continually assessing the AI's relevance and effectiveness in achieving

their desired educational outcomes. This dynamic interaction framework aligns with the principles of SCL and inquiry-based learning, as it encourages students to take control of their educational processes, actively questioning and reshaping the information provided by LLMs to better suit their learning needs. This comprehensive perspective shows how students continuously and autonomously engage with LLMs as interactive platforms.

Although this study's analysis within HAIC's metaphysical framework and Reeve's (2012) agentic framework for student engagement demonstrates that interaction with LLMs can significantly enhance student autonomy in learning, it also introduces certain risks. Currently, interactions with LLMs are predominantly student-driven and remain largely unregulated, giving students complete control over the prompting process. This autonomy, while beneficial in fostering independence, could be harmful if unsupervised and lacking in critical guidance and feedback. To address these concerns, higher education institutions should adopt a proactive approach in facilitating student interactions with LLMs. Eager and Brunton (2023) calls for greater support and guidance within higher education institutions to support students in navigating AI tools. This could involve organising workshops or sessions into curricula that guide students in leveraging AI effectively within a structured inquiry-based learning framework, integrating techniques from established prompt engineering models and drawing on SCL literature. Additionally, institutions could develop assessment criteria that focus not only on the end products of student work but also on the processes students employ in interacting with and utilising AI. These strategies should assess students' effectively managing limitations of AI tools and their ability to integrate AI-generated content with their original insights. This focus on process alongside product ensures a holistic evaluation of student engagement with AI, promoting a more effective and responsible integration of technology into the higher education learning experience.

Discussion of the Relational and Social Dimension

The relational dimension of HAIC and the social dimension of student engagement both emphasise the critical role of the social conventions in shaping meaningful interactions. While these dimensions operate in different contexts—the former in AI-specific interactions and the latter in traditional educational settings—both underscore the necessity of considering the social realities that form within students' processes of learning to improve engagement and interaction outcomes. The exploration of social affect within the context of AI in education is a new and unique phenomenon which unfolds within a broad ideological landscape of social learning theory and anthropomorphic design (Baker et al., 2023).

Whilst this study's findings does not present student relationships with LLMs as a conclusive social entity within student learning environments, akin to teachers and peers, it does provide evidence of the communicative resonance and social practices that are still being performed within prompts, highlighting this relational dimension that exists within instances of communication between students and LLMs. The relational or social dimensions of prompts in communication between students and LLMs were minimally represented compared to other dimensions explored. This study's findings identified 33 prompts (3.6%) from 9 unique participants out of 23 (39.1%) that incorporated traditional social elements of communication, aligning with the relational dimensions of HAIC and paralleling understandings from the social dimensions of student engagement literature. Notably, participants often exhibited practices of politeness and linguistic etiquette, including the use of courteous expressions such as "please" and "thank you".

> *"[insert relevant image]* ***please*** *report this in text, APA format.* ***thanks!****"*

> *"write me a table of contents for this dissertation* ***please****"*

Other prompts would facilitate conversation with the LLM in with other social mannerisms:

> *"hi chatgpt! please read through my essay and write a title for the essay, which shouldnt be longer than around 10 words long. can you do that?"*

The prompts directed at LLMs exemplify direct communication between humans and AI, where students employed conversational norms akin to traditional human-human interactions. For example, using queries like "can you do that?" students not only echoed concepts of human-AI resonance (Lomas et al., 2022), but also created a 'meeting place' of minds that facilitates mutual understanding of conventional human communications (Peters, 2006). These mannerisms are crucial in effective communication, relying on the conversational format of the chatbot interface and establishing norms that sustain relationships in both personal and professional contexts. This emphasis on manners, while not directly related to learning, serves as a bridge to understanding the larger role of social norms in learning contexts.

By employing manners with LLMs, these students were not only engaging with the technology as communicative subjects within their learning environments but were also participating in acts of social reciprocity and resonance, leading to the potential for new formations of social realities within students' educational environments (Donati, 2010). This can foster a deeper, more integrated level of engagement with LLMs as communicative subjects within their academic work and establish accountability and reflexivity within students' responses towards their own learning, further enhancing SCL outcomes. These considerations are evident in the development of LLM tools such as SimStudent, which attempts to evoke social reciprocity between student users and AI (Lorenz et al., 2016). Therefore, students' who utilised social practices of communications with LLMs engaged with them as a standard communicative

partner in the academic process, potentially enabling a deeper and more reflexive process of self-regulated learning.

Despite these observations, the data from this study indicates that social resonance with LLMs was uncommon within higher education settings. Among the participants, a significant majority (60.8%) did not exhibit any form of communication that involved relational interactions with LLMs. This pattern suggests a broader trend away from integrating social dimensions in the use of LLMs in educational contexts. As a result, the findings emphasise the predominance of functional and agentic interactions of HAIC in higher education. This suggests that the pedagogical implications of LLM use are primarily confined to enhancing cognitive and agency-related aspects of university student engagement, rather than fostering social connections. While these insights remain pertinent and are supported by a substantial body of literature advocating their future integration into AIED, this study's analysis reveals that the relational dimension of student adoption in higher education is significantly underrepresented.

Main Theme	Number of Prompts	Number of Participants	Subtheme	Number of Prompts	Number of Participants
Linguistic Manipulation	360	22	Thesaurus	72	9
			Rewrite	124	16
			Write	65	17
			Concept Integration	33	12
			Explain	47	16
			Search Input	19	5
Engaging with Corpus Data	245	21	General Questions	59	13
			Technical Questions	186	20
			Literature and Citing	60	10
			Quantitative Inquiry	49	7
Ideation	97	19	Exploration	38	13
			Feedback Request	59	14
Controlling the LLM	126	17	Response Tinkering	75	16
			Preparing GPT	11	3
			Specifying Format	40	12

Figure 2: Table of Engagements with LLMs. Outlines the number of prompts coded to each engagement category, as well as the number of participants who contributed such prompts.

Conclusion

In conclusion, this study sheds light on how students are adopting LLM technologies within their academic work, the pedagogical implications of the associated practices, and suggestions into the ways educational institutions can respond. This analysis contributes to the expanding body of literature on the utilisation of LLM technologies in higher education (Huang, 2023) (Dai et al., 2023) (Lee and Hannafin 2016) (Upadhyay et al., 2024) (Bernabei et al., 2023) (Chan and Hu, 2023). The data revealed that students were mainly utilising LLMs to recreate text with different linguistic representations and to draw

upon their corpus data as an informational resource. These fundamental methods of engagement enabled further strategies which provided precise value to students, such as assisting with ideation, citations, and quantitative tasks. Students were developing and applying self-regulated strategies in their prompts by identifying gaps in their knowledge, creating cognitive scaffolds, and engaging in operational reasoning. This study builds on the literature on prompt engineering for pedagogy (Denny et al., 2024) (Cain, 2024) (Walter, 2024) by illustrating how prompts serve as effective channels for pedagogical inquiry, enabling students to explore and apply self-regulated learning strategies. Furthermore, this study demonstrates that LLMs foster student autonomy by enabling them to direct the technology through specific prompts. This control positions students at the helm, allowing them to make informed decisions and shape the LLM's outputs according to their own judgements and needs. These findings illustrate how students' agentic engagements with LLMs are consistent with the principles of SCL, wherein stude*n*t agency is crucial for enhancing engagement and motivation (Klemenčič, 2017). Additionally, the analysis of prompts reveals that students critically assessed their generated responses, promoting learning processes that are iterative and constructive, aligning with practices of inquiry-learning (Sharples et al., 2019). Although less frequent, students also displayed polite behaviours and social reciprocity in their prompting activities which suggest a deeper engagement and establishing of LLMs within their pedagogical network, leading to SCL outcomes like increased reflexivity and accountability (Kahn et al., 2017).

This research underscores the need to enhance AI literacy within higher education curricula to mitigate the negative impacts of both the inherent limitations of LLMs and the flaws in the corpus data they utilise. This method resonates with and supplements a growing corpus of scholarly work promoting similar educational responses (Eager and Brunton, 2023) (Zdravkova, 2022) (Southworth et al., 2023). As AI tools increasingly facilitate such tasks, this study's data demonstrates that students were relying on the linguistic manipulation capabilities of LLMs, adding towards growing concern that students may become overly reliant on these capabilities for academic and professional writing. To counteract this, it is imperative that students are taught to master these cognitive skills independently, aspiring toward mastery in both the creation and comprehension of complex texts. A significant use of LLMs among students was for retrieving information from the model's extensive corpus data. In light of this, educational institutions should aim to elevate AI literacy standards by promoting a deeper critical understanding of corpus data and its limitations. This ensures that students recognize it as just one of many sources of information and approach it with the necessary criticality. Moreover, students were employing LLMs to brainstorm, gain insights, and receive feedback on their work. While this is beneficial, it is crucial that educational institutions maintain a regulatory role in guiding this usage. Ensuring that students retain their own creativity and critical thinking skills in the process is essential. Thus, this study contributes insights towards educational responses to the surge of AI tools in higher education students to ensure that LLMs can be used effectively without compromising the intellectual development of students.

There is significant scope for further research into students' social perceptions of LLMs. This study contributes to the broader academic discourse by collecting, analysing raw prompt text from students in higher education. This methodology offers tangible evidence of these interactions that can

support and enrich future investigations in this area. Despite this, additional evidence in the form of student interviews to explain their prompting intentions and strategies, as well as navigate their experiences with using the technology can bolster these conclusions.

It is no doubt that more and more students are engaging with LLMs in higher education, indicating that more and more text may be generated rather than authentically written. Amongst the sea of generated text, the prompts used by students represent the human effort and intentionality behind these creations, and should be analysed accordingly. As these AI technologies become more embedded in academic settings, institutions have a crucial role in ensuring their use aligns with educational objectives and ethical standards. Hence, this study provides informed insight from an analysis of students' prompts to assist educators, institutional policymakers and technology designers with the pedagogical integration of LLMs within higher education.

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Appendix

Pie Charts of Prompt Distribution

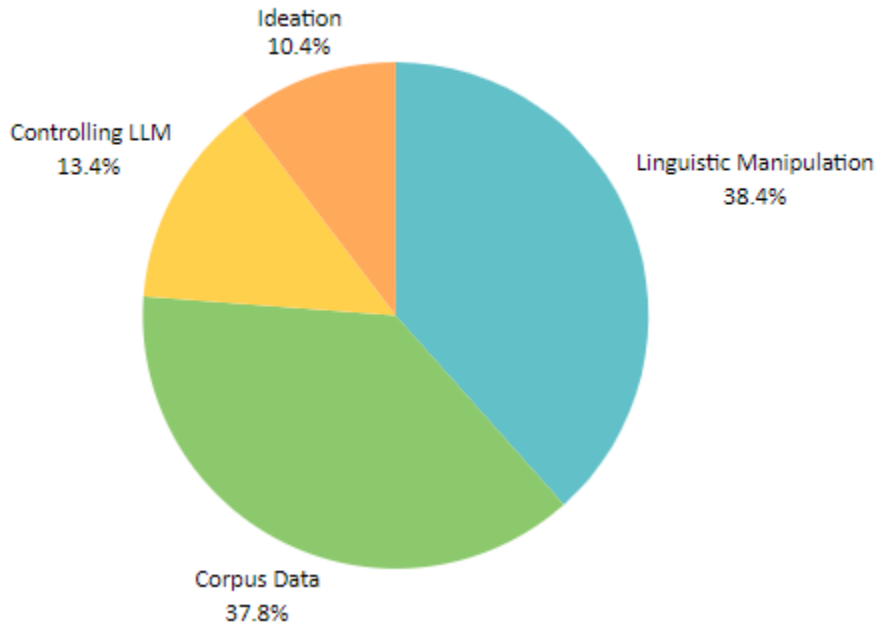


Figure 3: Pie chart depicting the distribution of prompts amongst the 4 main methods of engagement.

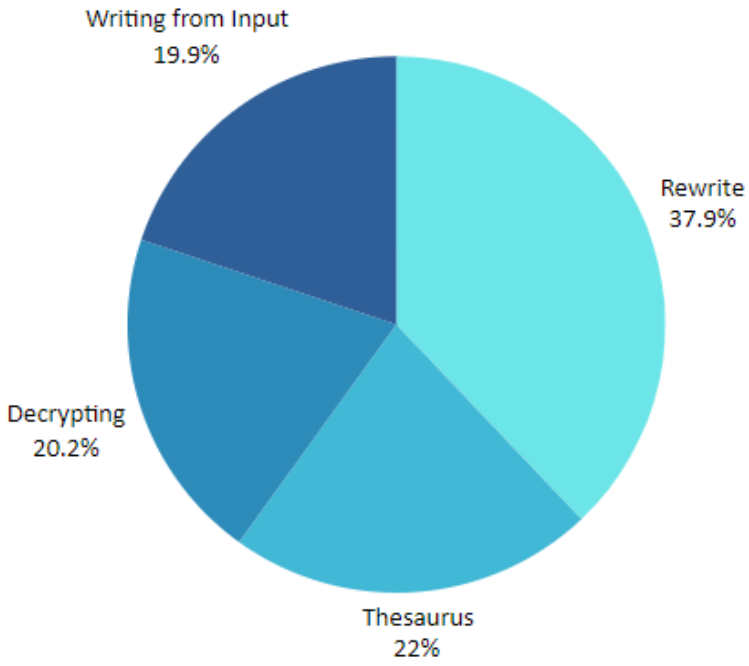


Figure 4: Pie chart depicting the distribution of prompts amongst the sub-categories of the Linguistic Manipulation engagement group.

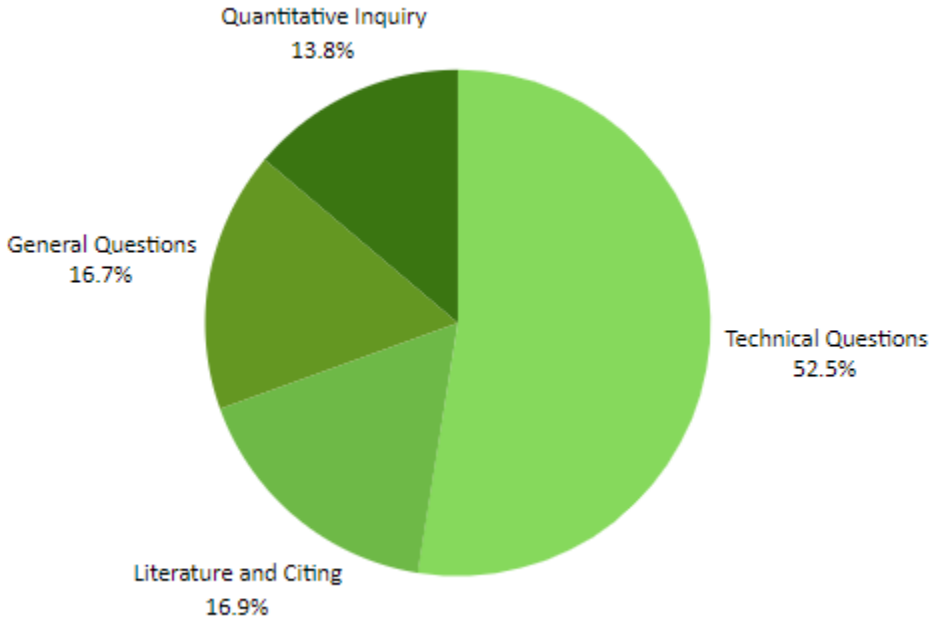


Figure 5: Pie chart depicting the distribution of prompts amongst the sub-categories of Engaging with Corpus Data engagement group.

Questionnaire

Questionnaire

Natural Language Instruction as an Emergent Linguistic Code for Higher Education Students using Large Language Models

* Required

Participant Biography

1

Age *

2

Gender *

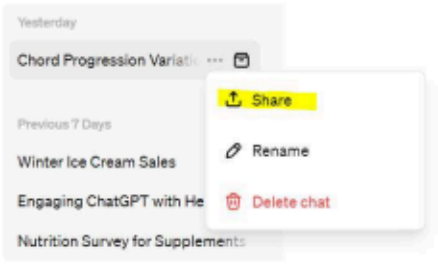
- ◯ Male
- ◯ Female
- ◯ Non-binary
- ◯ Prefer not to say

Participant LLM Context

3

Briefly summarise your academic background, including your current study: *

Chat Log Sharing



Please share a conversation with an AI-LLM which was **on the topic of your academic work.**

There are 2 ways to do this: using the **link share** function or **manually pasting**.

Please try to share 6 conversations.

1. Link share (the fastest):

- Most popular LLMs have a link share function which produces a link to the conversation that you can paste into the answer text box. This is definitely the fastest way to share your prompts. If you are copying in the link, please ensure anyone with the link can access the chat information.

2. Manual Pasting

- If there are particular moments in a conversation with the LLM that you are not comfortable sharing, you will have to copy and paste your prompts into the answer text box manually, omitting the prompts you don't want to share.

    - Note that there is a maximum character limit, to conserve text space, please paste in **only your prompts**, without any of the generated responses.

    - Please refrain from editing your actual prompts. Prompts should be shared untouched and in whole.

8

Conversation #1 *

9

Conversation #2 *

10

Conversation #3 *

CUREC

Dear Eric,

Thank you for your patience and cooperation during this review process.

I am writing to acknowledge receipt of your CUREC 1B application entitled '*Natural Language Instruction as an Emergent Linguistic Code for Higher Education Students using Large Language Models'*. The application was reviewed and approved by Dr Lulu Shi, your supervisor. No further approval from the Education DREC is required for applications reviewed under the CUREC 1B process. As such, the project will not receive a formal letter of ethical approval from the SSH IDREC.

The ethics reference for your application is C1B-24HT-Educ-023. Please add this reference to your CUREC 1B form and include it on documents for the research participants such as the participant information sheet.

Please note that this is contingent on the research project adhering to the criteria set out in the CUREC 1B guidance. Please ensure, therefore, that you comply with the conditions of this process and, should anything change in the course of the project, you should discuss this with your supervisor to determine whether this requires further review and approval by the Education DREC.

Please don't hesitate to get in touch if you have any questions.

All the best for your research – we hope it goes well.

Irina

Irina Lepadatu
Research Manager

Department of Education, University of Oxford
15 Norham Gardens, Oxford, OX2 6PY

Research SharePoint site

Participant Invitation Message

Hello! My name is Eric, I'm a masters student at the University of Oxford reading for an MSc in Education (Digital and Social Change). For my dissertation this year, I'm currently researching an exciting area of education and AI technology. If you're a university student who currently uses AI tools like ChatGPT to help with your academic work, then please consider doing this quick 10 minute questionnaire to help me with my research.

https://forms.office.com/Pages/ResponsePage.aspx?id=G96VzPWXk0-0uv5ouFLPkf_qCeHRylRMltOIShbA2OdURVJFSURWOVEyN0RSQkgyUTk0RUVOQlBHRy4u

My research focuses on understanding how university students are constructing prompts and conversations with generative AI language models, such as ChatGPT, Bard/Gemini or ClaudeAI. Aside from some basic information about your gender, age, academic background and usage habits with these models, you will be asked to share your prompts and conversations with the AI models that you use. These texts will be analysed from a linguistic and semantic perspective to better understand the ways

you have used language to communicate with the AI and the nature of your instructions. You will also be asked to share your academic background and your opinions and usage habits with generative AI tools. This information will be used to better inform the context of your prompts and conversations. Ultimately, my research aims to inform design and guidelines of these AI models in higher educational settings that constitutes responsible and effective use.

Your data will be handled in accordance to the University Guidelines (https://compliance.admin.ox.ac.uk/data-protection-policy#collapse1102266). It will be stored on the university's Microsoft Nexus365 OneDrive and will only be accessible to me and my supervisor.

For more information and to consent to participate in the study, please refer to the participant information sheet (link). Feel free to reach out if you have any more questions.

Thank you very much for your time and attention!

Contact

Main Researcher: Eric Xu

Phone: +44 73421*****

Email: sant6526@ox.ac.uk

Supervisor: Dr Lulu Shi

Email: lulu.shi@education.ox.ac.uk

Participant Info Sheet

Natural Language Instruction as an Emergent Linguistic Code for Higher Education Students using Large Language Models

CUREC Approval Reference:*C1B-24HT-Educ-023*

General Information

For my research, you are asked to complete a questionnaire which asks them to share prompts they have written into AI Large Language Models (LLMs) such as ChatGPT and Bard for their academic work. By collecting and analysing the prompts of university students, this research aims to gain a broader understanding of the real and current usage of these technologies within a higher education setting.

Prompt engineering refers to the practice of carefully constructing an instructive body of text using natural language for an AI language model to interpret and respond to. The engineering of this text aims to elicit a response from the AI model that is most appropriate to the prompters needs and devoid of any inaccuracies or biases that the AI model might produce. Thus, the ability for humans to effectively instruct complex AI models using natural language emerges as a significant digital skill in an era of AI LLM technology.

By exploring the linguistic behaviours of students in higher education using this technology, this research aims to provide a glance into how prompt engineering practices are evident and

common in student's usage of AI LLMs in their academic work. It also seeks to find other common habits or techniques which students tend to naturally adopt within these digital interfaces.

We appreciate your interest in participating in this questionnaire. You have been invited to participate as you are a student in higher education in the UK. Please read through this information before agreeing to participate (if you wish to) by ticking the ‘yes’ box below.
You may ask any questions before deciding to take part by contacting the researcher (details below).
The Principal Researcher is Eric Xu, who is attached to the Department of Education at the University of Oxford. This research is being completed under the supervision Dr Lulu Shi.

You will be asked to share your age, gender and academic background, but not any identifiable information such as your name. This will help establish a profile for different users of the AI LLMs and inform demographic analysis. Furthermore, you will be asked to share your habits, and attitudes towards AI LLM, as well as the prompts that you have written into these interfaces as part of your working process for your academic work.

My research will analyse these prompts in terms of their use of language and intention. Your prompts and conversations with the AI LLM will be closely analysed to understand the unique ways in which you instruct an AI LLM with natural language.

This is relevant for the research objectives of identifying how natural language instruction is informed by linguistic behaviour. Qualitative analysis of real user prompts from university students helps establish the specific forms and styles of communication that have emerged in utilising these technologies.

Do I have to take part?

No. It is up to you to decide whether to take part. You can withdraw yourself from the research, without giving a reason and without negative consequences, by advising me of this decision. The deadline by which you can withdraw any information you have contributed to the research is August 1st, 2024. If you choose to withdraw your questionnaire response, your data and any direct or indirect copies made of it will be deleted across all digital and physical platforms. It will not be analysed or included in any final research findings.

How will my data be used?

The findings from the research will be written up in my dissertation for my MSc programme at the University of Oxford. You will not be identifiable in the final version of the dissertation.

I would like your permission to use direct quotations of your prompts as well as your academic background in any research outputs, any other identifying features will be made anonymous in the final paper.

Your IP address will not be stored. We will take all reasonable measures to ensure that data remain confidential.

The responses you provide will be stored in a password-protected electronic file on University of Oxford secure servers and may be used in academic publications. Identifiable information will be deleted as soon as it is no longer required for the research.

Research data will be retained for at least 3 years after publication, but not personal data.

Who will have access to my data?

The University of Oxford is the data controller with respect to your personal data and, as such, will determine how your personal data is used in the research. The University will process your personal data for the purpose of the research outlined above. Research is a task that we perform in the public interest. Further information about your rights with respect to your personal data is available from https://compliance.admin.ox.ac.uk/individual-rights.
The data you provide may be shared with myself, the main researcher Eric Xu as well as my supervisor, Dr Lulu Shi.

Who has reviewed this research?
The application was reviewed and approved by my supervisor on behalf of the Departmental of Education's Research Ethics Committee. (Ethics reference: xxxxx).

Who do I contact if I have a concern or I wish to complain?
If you have a concern about any aspect of this research, please contact Eric Xu, (sant6526@ox.ac.uk) or Dr Lulu Shi (lulu.shi@education.ox.ac.uk) and we will do our best to answer your query. We will acknowledge your concern within 10 working days and give you an indication of how it will be dealt with. If you remain unhappy or wish to make a formal complaint, please contact the University of Oxford Research Governance, Ethics & Assurance (RGEA) team at rgea.complaints@admin.ox.ac.uk or on 01865 616480.

Please note that you may only participate in this survey if you are 18 years of age or over.
☐ I certify that I am 18 years of age or over
If you have read the information above and agree to participate with the understanding that the data (including any personal data) you submit will be processed accordingly, please tick the box below to start.

☐ Yes, I agree to take part