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EXPLORING HUMAN-AI COMMUNICATION IN ACADEMIC SETTINGS: INTEGRATING COMMUNICATION THEORY ELEMENTS TO INCREASE EFFICIENCY OF COMMUNICATION

Master’s Thesis

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We have written this Master’s thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

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In addition, in preparing this thesis, we utilized artificial intelligence tools, specifically ChatGPT, to ensure a more efficient research process and enhanced accuracy in our writing.

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Abstract

This thesis delves into the intricate dynamics of human-AI communication, focusing on the key elements of communication that enhance interactions within academic research settings. By identifying a gap in the application of communication theory to human-AI interactions, this study integrates key communication elements—encoding, decoding, feedback, and noise—to understand and improve the efficacy of these interactions. By employing a mixed-methods approach, the research involved an experiment with ChatGPT recruiting master's degree students, analyzing how clarity of expectations, task difficulty, and user engagement influence communication. The findings suggest that clear expectations significantly improve the decoding of AI communications, thus facilitating more effective interactions. Furthermore, the study underscores the role of AI in enhancing research effectiveness and efficiency, advocating for AI systems that are both responsive and adaptable to user needs. This thesis contributes to the field by suggesting practical approaches for integrating AI tools in academic environments. Future research directions include expanding the sample size and exploring multimodal communication to deepen understanding of the nuanced interactions in human-AI communication.

Introduction

In the rapidly evolving field of artificial intelligence (AI), the interplay between humans and AI systems is a critical area of study. As AI technologies increasingly integrate into various sectors of life, understanding the dynamics of human-AI communication becomes paramount. This is particularly true in environments where AI enhances human capabilities rather than replaces them. Therefore, we will take a closer look at the dynamics of the human-AI relationship by explicitly focusing on the key components of communication to find the possibilities to improve human-AI communication. To analyze the key elements of the communication theory in a particular context, finding a research gap in the literature is one of the crucial steps we take. Our thesis identifies a significant research gap: the need for a comprehensive application of communication theory in studying human-AI interaction. While existing research acknowledges the role of user expectations and satisfaction (Dave et al., 2023), there is a need for a more systematic approach that considers communication theory, particularly elements such as encoding and decoding processes, feedback, and noise (Taylor, 1962). These are crucial for understanding how information is exchanged and processed between humans and AI, influencing the effectiveness of such interactions.

This research will explore how the key elements framed by communication theory influence the quality of human-AI communication. This study will seek to answer the following research questions:

- How are clarity of expectations and task difficulty connected to the encoding and decoding processes in human-AI communication?
- What role does user engagement play in the effectiveness of human-AI communication in academic research settings?

Embarking on this scholarly journey, the aim of the research emerges from a keen interest in the evolving field of artificial intelligence, particularly within conversational dialogue systems. Delving into this domain, the authors will set forth several objectives to guide the inquiry and analysis throughout the chapters of this thesis. Firstly, we will aspire to discover the complex mechanics of generative AI (Brynjolfsson et al., 2023) and its application in modern chatbots (Jia, 2003), such as ChatGPT (Thorp, 2023, which represent a revolutionary step in conversational artificial intelligence. This exploration will begin with a thorough overview of artificial intelligence, tracing the progression from its foundational theories to the sophisticated algorithms that drive today's AI systems. As the narrative evolves, we will focus on understanding AI's specific functions and utilizations within dialogue systems. This includes breaking down the architecture of chatbots and examining their historical development to appreciate their current capabilities and potential future advancements (Hutapea, n.d.). Central to the study will be integrating communication theory into the framework of conversational dialogue systems (Taylor, 1962). This theoretical exploration seeks to bridge the gap identified in existing literature, where the role of communication theory often remains underexplored in the context of human-AI interactions.

This study will use a mixed-methods approach, integrating both quantitative and qualitative data. Twenty master's degree students from diverse academic backgrounds will participate in an experimental setup involving interactions with ChatGPT, an AI-driven communication tool. The study variables will be structured around pre-task and post-task surveys and an experimental task with the ChatGPT tool. The variables, such as AI background and clarity of expectations, will be categorized as input-type variables. In contrast, the ones like decoding quality and user satisfaction will be considered as output-type variables. This comprehensive approach will enable a robust analysis of the key components affecting human-AI communication.

By grounding the study in communication theory and employing a methodologically thorough approach, this research will not only fill the gap in the existing literature but also provide practical insights that can inform the design and implementation of AI systems across various domains. The findings of this study are expected to have implications for the development of more effective AI tools capable of supporting human users in a manner that is both understanding and communicative, enhancing the synergy between human intelligence and artificial capabilities. Ultimately, this research anticipates contributing to the broader discourse on artificial intelligence in academic and practical contexts. It is prepared to provide valuable insights that could guide future research in AI technologies and their applications in conversational dialogue systems.

Keywords: AI, Human-AI communication, Chatbots, ChatGPT, Communication theory

CERCS codes: S265 Press and communication sciences
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1. Theoretical Framework on Artificial Intelligence in Conversational Dialogue Systems

1.1 Artificial Intelligence Fundamentals: A Transition Towards Generative Models

The concept of intelligence, encompassing acquiring and applying knowledge and skills in complex environments, constructs the foundation of Artificial Intelligence (AI). John McCarthy officially introduced the term "Artificial Intelligence" during the Dartmouth Workshop in 1956, marking a pivotal moment in establishing AI as an academic discipline. This workshop laid the groundwork for exploring intelligent behavior in artifacts, with AI becoming synonymous with replicating the key elements of communication in machines.

Bellman defines AI as the "automation of activities we associate with human thinking," encompassing decision-making, problem-solving, and learning (Bellman, 1978). Charniak and McDermott contribute to the discourse by positioning AI as the "study of mental faculties through the use of computational models" (Charniak & Mcdermott, 1986). Rich and Knight add nuance by characterizing AI as the study of enabling computers to excel in tasks currently dominated by human proficiency (Rich & Knight, 1991). Winston offers a complementary perspective, emphasizing the role of computations in enabling perception, reasoning, and action within AI systems (Winston, 1992). Through these foundational perspectives, it becomes clear that AI seeks to imitate and enhance key human components of communication, opening avenues for innovative applications that extend beyond human capabilities.

Building on these foundational definitions, Nilsson extends the scope of AI, stating that it is "concerned with intelligent behavior in artifacts" (Nilsson, 1998). This perspective underscores the broader aim of AI, which goes beyond mere automation to encompass the imitation of intelligent behavior in machines. As AI evolves, the focus shifts towards creating machines that perform tasks and exhibit adaptive, problem-solving, and learning capabilities similar to human intelligence. It can be concluded that AI is a dynamic field within computer science. Its primary objective is the creation of intelligent machines capable of executing tasks associated with human thinking. These tasks include decision-making, problem-solving, and learning, ultimately contributing to developing artifacts that exhibit intelligent behavior.

Having established a foundational understanding of Artificial Intelligence (AI) and its multifaceted definitions, we now focus on a specialized subfield that encapsulates a paradigm shift in AI applications. While traditional AI models focus on task-specific functionalities, generative AI introduces a transformative dimension by autonomously creating novel content. This evolution from conventional AI approaches to generative AI reflects a shift from predefined, rule-based systems to models capable of autonomous creativity and adaptation. As we delve into the complications of generative AI, we explore how this subfield expands the horizons of human-AI interaction, shaping the dialogue between users and intelligent systems in innovative ways.

1.1.1 Generative AI

Generative AI, as a specialized subfield of artificial intelligence (AI), has witnessed a surge in interest in recent years due to its transformative developments in various domains, such as software development, text, and images (Brynjolfsson et al., 2023). This cutting-edge technology, marked by its capacity to produce content autonomously, introduces a perspective shift in AI applications, differentiating itself from traditional AI approaches. Traditional AI systems are typically designed for specific tasks and rely on predefined rules and datasets (Russell & Norvig, 1995). In contrast, generative AI models, as elucidated by Brynjolfsson et al. (2023), leverage techniques like Generative Adversarial Networks (GANs) and variational autoencoders to generate new, original content that was not explicitly programmed.

Miyazaki further contributes to understanding generative AI's impact by highlighting its applicability beyond IT (Miyazaki et al., 2024). The versatile nature of generative AI extends its influence to professionals in non-IT fields, emphasizing its potential to reshape workflows and problem-solving approaches across diverse industries. Moreover, generative AI's innovative capabilities have been expressed in creative content generation, where it can produce art, music, and even writing. This contrasts with conventional AI, which often needs more creativity and adaptability that characterize generative AI's autonomous content creation.

In summary, generative AI stands out in the AI landscape because of its capacity for autonomous content generation. Content generation makes it different from the task-specific models. Its transformative potential spans various sectors, impacting not only IT professionals but also those in non-IT fields, marking a shift towards more adaptive and creative applications within artificial intelligence. Generative models can produce innovative and human-like text formats, analyze and respond to natural language, and personalize content based on user input (Brynjolfsson et al., 2023). These capabilities pave the way for developing increasingly sophisticated chatbots, conversational AI agents designed to interact with users in a simulated dialogue.

1.1.2. Chatbots History and Architecture of Chatbots

This section lays the groundwork for our transition to Chatbots, where the focus shifts from autonomous content generation to the interactive capacities of AI systems. Understanding how we interact with AI and the core communication elements involved is crucial as we delve into chatbots. This understanding naturally leads us to explore chatbots' impact on creating meaningful conversations between humans and AI. As we start to explore the extensive history of chatbots, it's essential to define what these systems are clearly. Jia (2003) defines chatbots as “online human-computer dialogue systems that use natural language” (Jia, 2003). This definition helps us understand how chatbots facilitate smooth conversations between people and machines, and it guides our examination of how chatbot technology has evolved. The history of chatbots dates back to a fundamental question posed by Alan Turing in 1950: “Can machines think?” Turing introduced the “imitation game,” known as the Turing Test, to see if machines could mimic human thought (Turing, 1950). The significant development in chatbots began with Joseph Weizenbaum's creation of ELIZA in 1966 at MIT. ELIZA was one of the first systems that could imitate human conversation by using pattern matching and keyword identification (Weizenbaum, 1966). Since ELIZA, there has been continuous progress toward developing more sophisticated chatbots.

In recent years, chatbots have become increasingly popular, enhancing customer service by speeding up interactions and performing repetitive tasks (Dwivedi et al., 2021). They are now used in various fields, including education, mental health, and finance, offering 24/7 support and handling multiple conversations simultaneously, improving efficiency and customer satisfaction (Ashfaq et al., 2020; Adamopoulou & Moussiades, 2020). Prominent chatbots like Siri, Alexa, and Google Assistant are known for their broad functionality and widespread use. Table 1 illustrates the development of notable chatbots and their release

Table 1

Evolution of Chatbot Technology: 1966 - 2024

Name	Released year	Knowledge	Response Generation Method	Text Processing	Machine Learning Model	Dataset	Evaluation method
ELIZA (Achiam et al., 2024)	1966	Closed	Rule-based	Pattern matching	No machine learning	Not applicable (predefined rules)	Informal user interaction observations
Cleverbot(Rahman et al., 2017)	1995	Open	Learning from user inputs	Pattern matching, AI algorithms	Various algorithms	User interactions	Informal user satisfaction, ongoing learning from conversations
SmarterChild (Bibault et al., 2019)	2001	Closed	Rule-based	Pattern matching	No machine learning	Not applicable (predefined rules)	Informal user interaction observations
Mitsuku (Croes & Antheunis,2021)	2005	Closed	Rule-based	Pattern matching	No machine learning	Not applicable (predefined rules)	Informal user interaction observations
Amazon Alexa (Amazon Alexa, 2023)	2014	Open	ML models	Natural Language Understanding (NLU)	Proprietary models	User interactions	User feedback, performance in real-world scenarios
Google Assistant (Sari et al., 2020)	2016	Open	ML models	NLU	Proprietary models	User interactions	User feedback, performance in real-world scenarios
IBM Watson Assistant (Kumar et al., 2022)	2018	Open	ML models	NLU, Intent Recognition, Dialogue Management	Watson Assistant	Customizable, user-specific data	User feedback, accuracy in understanding and responding
GPT-2 (Ali et al., 2023)	2019	Open	Transformer-based language model	Deep neural networks	Large, diverse datasets	Various sources, including internet text	Language modeling benchmarks, qualitative assessment
GPT-3 (Ali et al., 2023)	2022	Open	Transformer-based language model	Deep neural networks	Broad internet-sourced data	Various sources, including internet text	Language modeling benchmarks, qualitative assessment
ChatGPT (Ali et al., 2023)	2023	Open	Transformer-based language model	Deep neural networks	Diverse internet-sourced data	Various sources, including internet text	Language modeling benchmarks, user feedback

Source: Cited in the “Name” column of the table dates, highlighting the evolution of conversational AI. This evolution shows that chatbots have significantly advanced from their basic beginnings to become integral in many areas of life. Chatbots' effectiveness relies on the data they are trained with. It emphasizes the need for good training data to build machine learning models for generating responses or to create databases for retrieving information. These databases' ongoing improvement and expansion support algorithmic advancements, enhancing chatbot interactions to be more like humans.

In the early days, chatbots like ALICE used simple, rule-based methods with manually curated knowledge bases (Wallace, 2009). Later, the approach shifted to using large, annotated dialogue datasets. More recently, the trend has moved towards using scraped online dialogues, allowing for the automated creation of extensive knowledge bases essential for modern chatbots (Hutapea, n.d.). Additionally, "federated learning" is a technique where there is no need for online materials; instead, the model is developed and trained directly on a local device and then sent to a central server—not the data, which might be confidential, but only the developed model. In other words, federated learning represents a method to train AI models while ensuring that no one has access to or manipulates your data, providing a secure approach to harness information for powering new AI applications (Mammen, 2021).

Modern chatbot architecture is characterized by several foundational elements that collectively contribute to their functionality (Hutapea, n.d.):

- Knowledge (Open or Closed Domain): Specifies whether the chatbot is designed for a broad range of topics (open domain) or is tailored for specific subject areas (closed domain).
- Response Generation (Retrieval or Generative): Defines how the chatbot formulates replies by retrieving pre-existing responses or generating new ones through algorithms.
- Text Processing (Vector Embedding or Latin Alphabet): Refers to the techniques employed for handling and understanding text, encompassing approaches like converting words to numerical vectors (vector embedding) or traditional language-based processing using the human-invented alphabets.
- Machine Learning (ML) Model: Encompasses machine learning, often leveraging neural networks, to enhance the chatbot's ability to comprehend and respond to user inputs.

The creation of chatbots involves various strategies, one of which is the Human Imitation Strategy, significantly impacting AI-human interaction. Pereira proposed strategies such as Personality Development, Directing the Conversation, Small Talk, and Human-like Failures that contribute to making bots appear more human (Hutapea, n.d.). Utilizing natural language processing (NLP) methods, including keyword extraction and part-of-speech (POS) tagging, chatbots use linguistic analysis to infer the user's goals at each turn of speech. These goals are added to a goal stack associated with specific contexts, and bots employ context-based reasoning (CxBR) to direct their responses. As goals change, contexts evolve, influencing the bots' communication style (Hung et al., 2009).

Contemporary chatbot architecture undergoes continuous refinement, incorporating and advancing based on its fundamental components:

- Dataset: Comprises the set of examples or inputs used for training and fine-tuning chatbots, shaping their performance and capabilities.
- Evaluation Model: Encompasses the methodology or criteria employed to assess chatbot effectiveness, involving metrics like accuracy, user satisfaction, or performance in specific tasks.

Before delving into the specifics of ChatGPT, the subsequent table will further explore the historical technicalities of chatbots, providing a comprehensive foundation for the ensuing discussion. Table 1 provides a condensed overview of Chatbots, spanning from their initial release in 1966 to the present year, 2024.

1.1.3. ChatGPT: A Revolutionary Chatbot in Conversational AI

The improved version of the generative pre-trained transformer (GPT) architecture incorporates the basis of the contemporary AI technology known as "ChatGPT". The mentioned progressive architecture is characterized by its excellent emergent abilities. One of those abilities is creating complex and tailored behaviors suitable for various applications by sticking to instructions. Consequently, ChatGPT excelled over its predecessors in capabilities (Gabashvili, 2023). ChatGPT is a notable chatbot in the modern landscape, showing a remarkable improvement in conversational artificial intelligence. This language model, grounded in Reinforcement Learning from human feedback, is designed explicitly for producing engaging and coherent conversational outputs (Thorp, 2023). Its emergence has not only gotten widespread recognition. Still, it has also established itself as a popular choice owing to its impressive ability to generate realistic responses across various topics (Lund & Ting, 2023).

With the evolution of GPT-4, OpenAI's most advanced large language model, businesses are presented with a powerful tool capable of excelling in creative content generation. This adaptable chatbot seamlessly integrates into existing frameworks, offering extensive customization options that streamline operations, reduce costs, and enhance overall efficiency. The introduction of GPT-4 into various industries marks a significant step forward in harnessing the potential of advanced language models for practical applications (Bubeck et al., 2023). However, like any sophisticated technology, GPT-4 has its challenges. Despite its capabilities, occasional inaccuracies and inherent biases raise concerns about the reliability of its outputs. Moreover, GPT-4 exhibits limited contextual awareness, emphasizing the need for attentive oversight to ensure the accuracy and appropriateness of its responses. A notable drawback is the need for real-time updates in GPT -4's knowledge base, which may present obstacles in dynamic business environments where up-to-the-minute information is essential (Achiam et al., 2024). Additionally, the system's susceptibility to inappropriate queries poses potential risks to data security, demanding careful consideration in its deployment.

GPT-4 offers tailored solutions that cater to the specific needs of businesses. On the other hand, its challenges, particularly regarding accuracy, real-time updates, and security considerations, underscore the importance of a cautious and strategic approach. Considering the transformative potential of integrating the GPT-4 into various sectors, careful attention is paid to addressing these challenges and continually refining its capabilities. As we navigate the complexities of ChatGPT's functionalities and limitations, the subsequent sections will further explore its impact on human-AI interaction and the evolving dynamics of AI technology in contemporary discourse.

1.2. Functions and Usage of AI in Conversational Dialogue Systems

AI has become an integral part of our daily lives. Its influence is especially evident in the conversational dialogue systems. These systems allow machines to engage in meaningful, human-like exchanges through the use of sophisticated algorithms and capabilities ((Haleem et al., 2020); (Cuzzolin et al., 2020); (Rai, 2020)). A key goal of AI within these systems is to provide intelligent perception, decision-making abilities, and the components of communication that mimic human thought processes (Y. Xu et al., 2021).

Let us examine how AI enhances conversational dialogue systems:

- Instant and Automated Responses: AI-powered systems respond quickly and automatically to user queries, using algorithms to analyze input and generate relevant responses (Xu et al., 2021; Wollny et al., 2021).
- Natural Language Communication: AI plays a critical role in enabling these systems to understand the subtleties of human language, allowing for natural interactions beyond rigid, computer-like exchanges (Russell & Norvig, 1995).
- Customer Service Enhancement: AI-infused agents excel in customer support, providing 24/7 assistance and tailored responses, significantly improving customer satisfaction (Song & Xiong, 2021).
- User Experience Optimization: AI is vital in crafting intuitive and seamless user experiences within conversational dialogue systems (Song & Xiong, 2021). AI algorithms tailor interactions by understanding a user's needs and preferences, enhancing engagement and overall satisfaction.
- Adapting to User Preferences: AI-powered dialogue systems can "learn" from user interactions. They continuously analyze patterns and behaviors, adapting their responses accordingly (Lin et al., 2023). This dynamic evolution allows for highly personalized recommendations and a context-aware approach that separates these systems.
- Information Retrieval and Dissemination: AI offers powerful tools within conversational systems to access and process vast amounts of information. This facilitates efficient information retrieval and knowledge sharing, empowering users to find relevant and accurate answers to their questions easily (Lin et al., 2023).

The potential of conversational AI extends beyond immediate customer engagement. Its ability to revolutionize customer service, personalize learning experiences, and streamline interactions has transformative potential across e-commerce, education, healthcare, and beyond ((Song & Xiong, 2021); (Lin et al., 2023)). AI is the driving force behind the sophisticated conversational dialogue systems we encounter today. AI is revolutionizing our interactions with machines by integrating natural language processing, rapid response generation, personalization, and knowledge access. As this technology continues to evolve, we can anticipate even greater innovation and more seamless integration of conversational AI systems into our daily lives, further solidifying the partnership between human and computer communication. At the heart of this exploration lies the burgeoning interest in AI applications, with Borges, Trimi and Berbegal-Mirabent spotlighting the competitive advantage AI systems bestow upon organizations (Borges et al., 2021; Berbegal-Mirabent & Trimi, n.d.). Through decision support, engagement enhancement, automation, and innovation in products and services, these systems equip businesses to navigate market complexities with unprecedented agility (Borges et al., 2021). However, realizing this competitive edge requires more than just deploying AI technologies; it demands a thorough assessment of an organization's readiness, a roadmap for integration, and a culture conducive to AI's adoption.

As Kordon (2020) discussed, Sahin et al.'s research introduces a critical preliminary step—evaluating an organization's readiness for AI, which hinges on technological infrastructure, data quality, organizational culture, and employee capabilities. This evaluation is crucial in identifying gaps that may impede AI implementation (Borges et al., 2021). Concurrently, Imsland and Sindre's study emphasizes the necessity of a strategic roadmap for AI integration, advocating for a methodical approach to embedding AI into business processes, thus ensuring value creation through gradual impact (Kordon, 2020). Beyond readiness and strategic planning, building a supportive organizational infrastructure emerges as fundamental. Trimi and Berbegal-Mirabent underscore the importance of fostering an AI-embracing culture, clarifying roles for AI implementation, and promoting effective collaboration between humans and AI systems (Berbegal-Mirabent & Trimi, n.d.). This infrastructure is central to implementation success and sustaining AI's integration into organizational processes as the narrative transitions from organizational strategies to individual and collective behaviors, illuminating the competencies and behavior patterns crucial for AI utilization (Wamba-Taguimdje et al., 2020). Understanding AI's capabilities and limitations, developing data literacy, prioritizing ethical AI use, and adopting a growth mindset are cornerstones for effectively leveraging AI. These competencies enable organizations and individuals to implement AI solutions, adapt, and innovate within the ever-evolving AI landscape.

At the forefront of AI's practical applications is its role in redefining customer service. Brandtzaeg and Følstad have illuminated how AI-powered chatbots have transcended traditional service boundaries (Brandtzaeg & Følstad, 2017). These digital assistants, equipped to understand and respond to user queries in real-time, offer personalized customer experiences, increasing customer satisfaction and engagement. Their deployment across various customer service platforms exemplifies AI's capacity to streamline operations and forge deeper customer connections through personalized interactions. The agility and efficiency of chatbots in handling queries underscore AI's potential to enhance customer service paradigms significantly. AI's influence extends into the fashion industry, pioneering personalized shopping experiences. As James highlights, AI systems, like the one developed by H&M, are revolutionizing how consumers engage with fashion (James & Montgomery, 2017). By analyzing users' preferences, past purchases, and even social media content, these AI advisors can offer bespoke fashion advice, suggesting outfits that align with individual styles and preferences. This streamlines the shopping experience and introduces a level of personalization previously unattainable, demonstrating AI's capacity to innovate and personalize within the retail sector.

One of AI's most profound impacts is observed within the healthcare sector. The collaborative research by Xu et al. reveals AI's pivotal role in transforming healthcare delivery and management (A. Xu et al., 2017). From diagnostic algorithms that enhance the accuracy and speed of patient evaluations to AI-driven operational tools that optimize hospital resource allocation, AI is at the heart of the transition towards more efficient, effective, and personalized healthcare services. Its application in developing predictive models also allows for better patient care by anticipating health events before they occur, thereby enabling preventative measures. This improves patient outcomes and significantly reduces the operational strain on healthcare systems, illustrating AI's critical role in advancing medical care and operational efficiency. These diverse applications of AI—from enhancing customer service and personalizing the retail experience to revolutionizing healthcare delivery—demonstrate the practical realization of theoretical AI benefits. As AI continues to evolve and integrate into various sectors, its potential to innovate, transform, and improve operational efficiencies and quality of life becomes increasingly evident. By bridging the gap between theoretical potential and practical application, AI reaffirms its status as a pivotal technology of the 21st century, capable of driving significant advancements across multiple domains.

1.3. Communication Theory in the Context of Conversational Dialogue Systems

Our journey through the integration of Communication Theory into Human-AI interaction embarks from the foundational understanding of the core components of communication that animate these exchanges. Following Taylor's seminal work in "A Model for the Communication Process," we recognize communication as a complexly layered activity that spreads across various dimensions (Taylor, 1962). Taylor's theory builds upon the SMCR model, which consists of four components: source, message, channel, and receiver.

The source formulates a communicative intention and encodes it into a message. The message is transmitted through a channel to the receiver, who decodes it and reacts accordingly. Taylor's statement that every message involves a code highlights these key elements of communication's critical role in AI's capacity to understand and generate responses. This idea grounds our exploration of the SMCR model as a lens through which to view ChatGPT's conversations.

As we navigate further, the literature reveals the challenges inherent in human-AI communication, where Taylor's insights into the influence of the receiver's attitudes and the nuances of decoding skills come to the forefront. Taylor suggests that communication effectiveness is significantly conditioned by these attitudes, a concept that resonates deeply within the interface between humans and AI (Taylor, 1962). This revelation points to the need for AI systems to simulate human communication elements and customize their interactions to align with individual user preferences and expectations. This notion is also supported by Dafoe, who emphasizes the importance of communication in fostering mutual understanding and coordination (Dafoe et al., 2021).

Progressing to the strategies aimed at enhancing human-AI dialogue, we draw from Amershi's recommendations, highlighting the necessity for AI systems like ChatGPT to articulate their capabilities and limitations effectively (Amershi et al., 2019). This strategy resonates with Jordan's concept of involved communicators, who leverage focused attention and a robust knowledge base to interpret meanings accurately and construct responsive dialogues (Jordan, 1998). Integrating human-like communication features, such as emotional displays and gestures, is highlighted as a transformative approach that significantly enriches the interaction dynamics between humans and AI (De Keyser et al., 2019).

The narrative then transitions to underscore the essence of incorporating insights from core elements of communication into the development of AI systems. Embracing perspectives from cognitive science and communication studies enables developers to craft AI that not only processes natural language with enhanced proficiency but also engages in dialogues that mirror human communicative norms more closely, embodying the vision of Rezwana & Maher (Rezwana & Maher, 2023). This approach is inspired by Sonnenberg's claim that effective communication is the cornerstone of collaborative creativity, guiding the path toward AI systems capable of empathetic and meaningful interactions (Sonnenberg, 1991).

To conclude our scholarly exploration, linking theoretical insights from communication theory and cognitive science with the practical demands of AI development is crucial. Applying these theories to analyzing human-AI interactions, particularly in the context of ChatGPT, reveals a landscape rich with challenges and opportunities. This synthesis of academic perspectives lays a solid foundation for exploring the cognitive dimensions of communication in human-AI dialogues.

1.4 Revisiting Literature: Unraveling the Variables in Human-AI Interaction

Understanding the intricate dynamics between individuals and artificial intelligence (AI) systems has become paramount in the evolving human-AI interaction. Communication theory serves as a guiding framework, shedding light on the exchange of information and the nuances of interaction. Taylor's communication theory underscores the essence of effective communication, emphasizing clarity and mutual understanding (Taylor, 1962). This framework extends seamlessly into the realm of AI interactions, providing a lens through which the effectiveness of communication between humans and AI systems, such as chatbots, can be evaluated.

As we learned more about human-AI interaction, the analysis of computer-mediated communication emerged as a critical avenue for exploration (Hill et al., 2015). Chatbots, a prominent manifestation of AI systems, have reshaped the digital communication landscape. Studies reveal that interactions with chatbots often extend longer than human conversations, yet they lack the richness of vocabulary and emotional depth inherent in human discourse (Hill et al., 2015). This distinction underscores the need to examine how communication theory informs the design and evaluation of AI-mediated interactions. User expectations form a cornerstone in the edifice of human-AI interaction, significantly shaping user satisfaction and interaction quality (Vilone & Longo, 2020). Studies underscore the influence of user attitudes toward AI on their experiences, highlighting the pivotal role of clear explanations and seamless interaction in fostering positive perceptions (Vilone & Longo, 2020). However, the impact of task difficulty on user expectations and satisfaction still needs to be explored. The perceived challenge of tasks may mediate user motivation, thereby influencing interaction outcomes (Spielberg & Azaria, 2022). Biometric sensors offer a promising avenue for assessing perceived task difficulty, providing insights into user states, and facilitating adaptive interventions (Alexandru & Gall, 2018).

Amidst the intricacies of human-AI interaction, the phenomenon of response verification emerges as a focal point of inquiry (Hamm et al., 2023). User behaviors in verifying AI-generated information are influenced by trust, system transparency, and perceived usefulness (Hamm et al., 2023). Explanations are vital in enhancing user trust and facilitating thorough engagement with AI systems (Hamm et al., 2023). The degree of perceived explainability impacts user trust and influences perceived usefulness and ease of use, thereby shaping interaction outcomes (Hamm et al., 2023). Moreover, user satisfaction is a barometer of successful human-AI interaction, influenced by prior experience and system performance (Dave et al., 2023). Individuals with previous experience tend to harbor higher expectations when engaging with AI systems, underscoring the importance of familiarity in shaping user perceptions (Dave et al., 2023). Education level, however, exerts little effect on user expectations, highlighting the nuanced interplay of various factors in shaping interaction outcomes (Dave et al., 2023).

Taking other people's views into account is very important in how we talk to each other and becomes even more important when we interact using AI (Baker-Brunnbauer, 2021). AI tools can help us see different points of view by giving us information from many places. However, they might also limit the variety of views we get because they often show us content that they think we will like (Baker-Brunnbauer, 2021). This shows why we need to be careful about the ethics of how AI is made and used, making sure these systems help rather than get in the way of understanding different perspectives (Baker-Brunnbauer, 2021). Mixing communication theory with actual research seems good for helping us learn more about how humans and AI interact. This way of looking at things shows us how clear goals, how hard tasks are, how we check answers, how happy users are, and how we understand different views are all important in talks between humans and AI. Despite this progress, many areas still need further investigation to understand this interaction fully. Researchers and experts use communication theory to explore new regions of human-AI interaction. They shed light on previously unknderstood aspects as they move forward, helping us gain deeper insights into how humans and AI communicate. This exploration of human-AI interaction through various studies highlights the importance of communication theory. Each study offers unique insights that enhance our understanding of the critical factors. Researchers are encouraged to venture further into this lesser-known territory of human-AI interaction. As we continue to uncover new information and address unanswered questions, communication theory serves as a crucial guide, helping us navigate through the complexities of this field and aim for a deeper understanding of these interactions.

In our research in human-AI interaction, communication theory acts as a guiding light, helping us explore many possibilities and leading us toward a more detailed understanding of how humans and AI interact.

2. Empirical Study on the Role of Key Elements of Communication in Human-AI Communication

2.1. Research Methodology and Process

Embarking on the empirical segment of this thesis, we delve into the nuanced interaction between human communication and artificial intelligence within conversational dialogue systems. This exploration is pivotal to understanding how users interact with and perceive AI technologies, particularly in settings that mimic real-world academic research. The choice of research methodology is also critical in framing the insights we aim to uncover. We have adopted a structured experimental approach designed to capture the cognitive dynamics in human-AI communication. This methodology allows us to carefully analyze the interactions between participants and AI, focusing on how different cognitive factors influence the effectiveness of these interactions.

The following sections explain our methods, outlining each step from participant selection to data collection and analysis. In the "Participants" section, we describe the diverse individuals involved in this study. The "Instruments and Procedures" section details the tools and protocols used to experiment. The section includes the surveys and interactive tasks with ChatGPT, designed to elicit behaviors and responses that reveal underlying cognitive processes and user strategies when interacting with AI. As part of this section in the study, the authors drew their study process to give a clear picture of the research process from beginning to end, including every step they had to take. Data collection and analysis are crucial components of our research, described thoroughly in their respective section. The strategies employed for gathering and examining data are intended to ensure the accuracy and integrity of our findings while also allowing for a comprehensive understanding of the complex dynamics at play.

Results and discussion form the core of the empirical study, where we present and interpret the data collected. This section aims to bridge the theoretical aspects discussed earlier with practical insights from the empirical evidence. We explore how the data aligns with existing communication theory and what new understandings we can derive from our analysis. The implications of our findings are discussed in depth, considering how they contribute to the existing body of knowledge and what they suggest for the future use of AI in educational and research contexts. This discussion extends into the "Limitations and Future Research" part, where we critically assess the constraints of our study and propose directions for further inquiry that could expand on our initial findings. Concluding the empirical part of the thesis, we reflect on the overall contributions of the empirical study. This conclusion synthesizes the insights gained, emphasizing their relevance to academic research and practical applications in AI-enhanced communication tools.

2.1.1. Instruments and Procedures

Before presenting the detailed process of our empirical study in the diagram below, it is important to outline the structured approach that was followed. The study began with a thorough literature review on artificial intelligence, particularly its use in communication systems, to establish a strong theoretical foundation. This was followed by examining past experiments on AI and human interactions to refine our methodologies and research questions. The empirical study was then methodically designed, focusing on relevant variables and the development of tailored surveys and tasks. The subsequent stages included participant recruitment, data collection, and rigorous analysis to ensure the effectiveness of our study in exploring human-AI communication within academic settings. The diagram Figure 1 illustrates these steps, from the initial literature review to the final discussion, highlighting how each phase contributed to a comprehensive understanding of the key aspects involved.

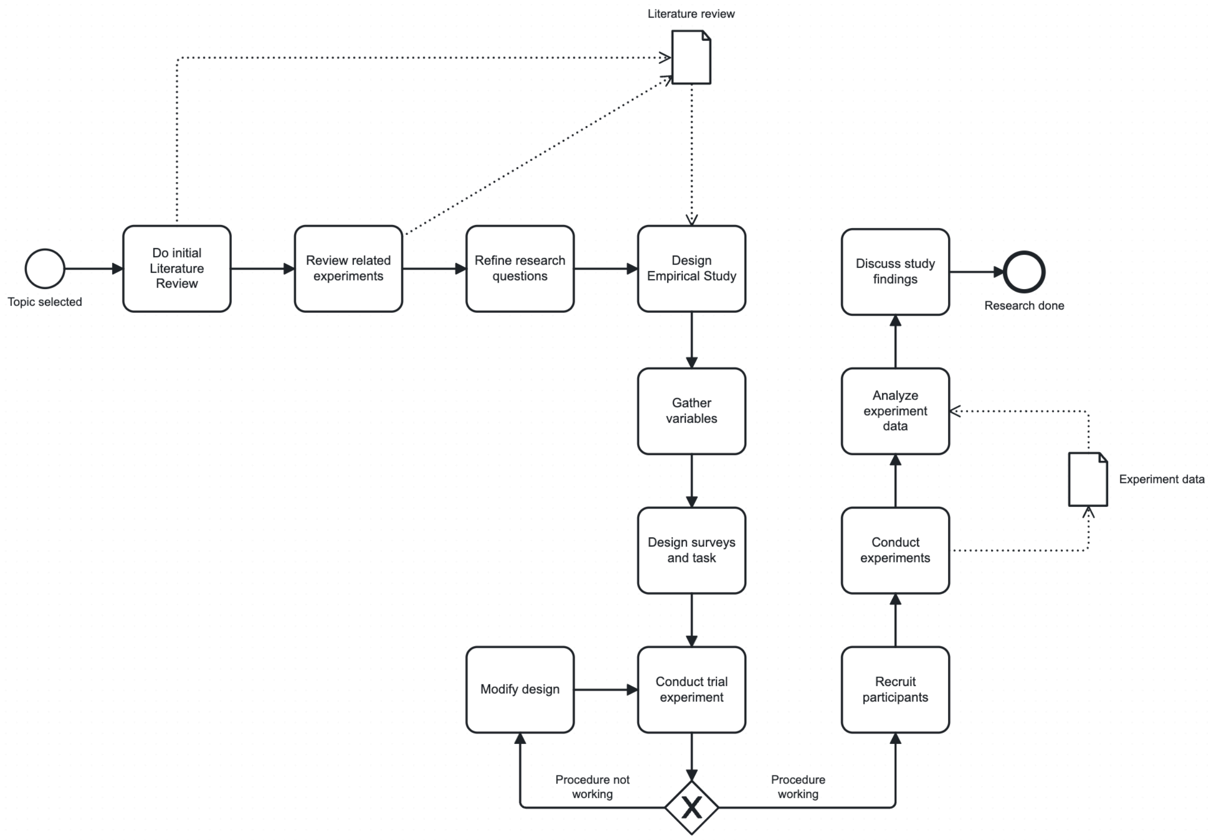


Figure 1. Study Process Diagram

Source: Created by the authors

Our empirical study was carefully crafted to explore the interactions between participants and artificial intelligence, explicitly using ChatGPT. Drawing inspiration from a significant study conducted by Harvard Business School in collaboration with Boston Consulting Group (Dell'Acqua et al., 2023), we recognized the transformative potential of AI in improving task efficiency and quality. This prior research, which revealed substantial productivity gains when knowledge workers used AI, guided our experimental design, encouraging us to harness similar AI capabilities in an academic setting.

Central to our methodology were two primary surveys, the pre-task and post-task surveys. These were designed to capture comprehensive data on participants' interactions with AI before and after the experimental task. By being administered through a secure online platform, these surveys facilitated the convenient participation of individuals from diverse locations, adapting to their varied schedules. The pre-task survey was the initial survey that gathered demographic data such as age, gender, and field of study and evaluated participants' prior experiences and comfort levels with AI technologies. The questions were carefully crafted to assess participants' expectations and preconceived notions about AI's capabilities in supporting academic research. There were open, leading, Likert scale type of questions. Following the experimental task, the Post-task Survey assessed participants' experiences with AI during the task. It included questions about the relevance of AI responses, the ease of interaction, and any challenges encountered. This survey was crucial in collecting detailed feedback on participants' satisfaction and perceptions of AI's effectiveness as a research tool. Here, by being more with the number, Likert scale type and open questions were dominating.

The core of our study was an interactive task facilitated by ChatGPT, which was aimed at mirroring real-world academic research processes. We provided ChatGPT with detailed guidelines about our research objectives, the time constraints, and the participant qualifications. From several potential tasks generated by ChatGPT, we selected one that best suited our study goals:

- Topic Selection: Participants began by choosing a research topic of personal or professional interest. This approach was designed to enhance participant engagement by ensuring the relevance of the subject to their contexts. To facilitate this selection process, the study provided examples of potential research topics while also allowing participants the autonomy to choose their topics independently. This method helped to maximize the motivation and contextual applicability of the research findings.

- Interaction with ChatGPT: In this phase, participants interacted with the AI to refine their research questions and explore possible methodologies. This step was pivotal in understanding how AI can assist in the conceptual phase of academic research.
- Outline Creation: Based on the interaction, participants crafted a brief research outline, including a problem statement, potential research questions, and an envisioned methodology.

This structured task was designed to evaluate the AI's utility in a typical academic research workflow and assess participants' ability to integrate AI-generated insights into a coherent research plan. Our experimental design and the surveys were deeply rooted in well-established communication theories, notably proposed by Taylor (1962) and Canary & McPhee (2011). These theories helped shape the structure of our task and the formulation of survey questions, ensuring that our study was theoretically sound and practically relevant. By focusing on key factors that influence human-AI interaction, particularly in academic settings, we crafted instruments that thoroughly assessed the dynamics of these interactions. This approach was crucial in exploring the key elements of communication that influence effective human-AI communication, thereby enhancing the integration of AI in academic research settings.

2.1.2. Participants

Our structured approach ensures that each participant is fully informed and actively engaged throughout the study, from recruitment to completion. The process begins with recruitment and informed consent, where participants are informed about the study's objectives and their rights. This is followed by a pre-task survey that gathers initial data on the participants' background and their expectations of AI. The main part of the study involves a task where participants interact with ChatGPT to develop a research outline guided by their chosen topic and discuss methodology. Finally, a post-task survey collects feedback on their experience, focusing on the AI's performance and the participants' satisfaction. The following diagram, Figure 2, illustrates these steps in detail, providing a clear visual representation of the participant journey in our study.

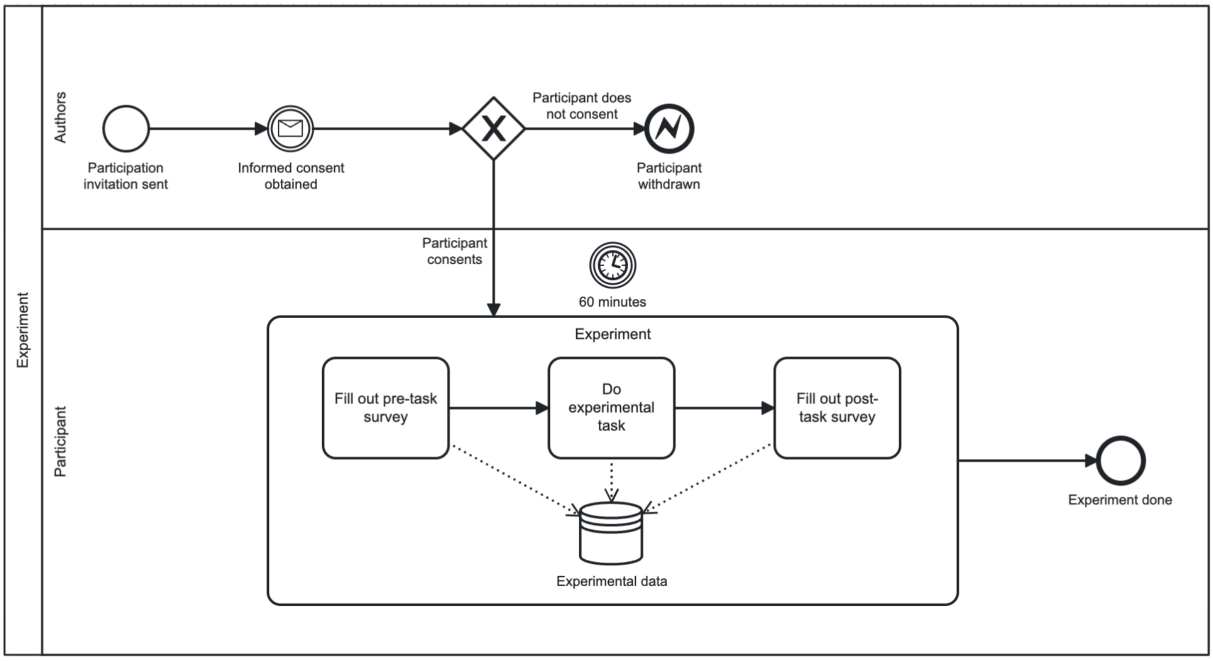


Figure 2. Participation Process Diagram
Source: Created by the authors

This empirical study explores how master's degree students from diverse academic backgrounds interact with and perceive AI technologies within the context of academic research. The empirical study involved a diverse group of twenty master's degree students studying at the University of Tartu. The participants were specifically selected to represent a broad spectrum of academic disciplines and backgrounds. The participants ranged in age from 20 to 33, providing a good mix of younger and more mature students. The gender distribution was somewhat balanced, with eleven males and nine females participating in the study. Each participant was informed about the study's objectives and the voluntary nature of their participation. Informed consent was obtained from all participants, ensuring they understood their rights, including the ability to withdraw from the study without any consequences.

Participants were selected using a purposive sampling technique. This method was chosen to ensure that the study included individuals actively engaged in academic research who could provide informed feedback on using AI tools in an academic setting. The purposive selection was also aimed at gathering insights from students with varying levels of familiarity and comfort with AI technology, enriching the study's data with a wide range of experiences and perspectives. This approach was deliberate to observe the influence of individual differences in AI exposure on how students interact with, evaluate, and form opinions about AI tools.

2.1.3. Data Collection and Analysis

In our empirical study on human-AI communication, we employed a robust data analysis approach to analyze both quantitative and qualitative data from pre-task and post-task surveys, along with AI interactions. We used inferential statistics to identify trends and patterns in participant behavior. For ordinal data, such as responses on Likert scales, we utilized Spearman's rank correlation analysis, which is well-suited for non-normal distributions, to determine the strength and direction of associations between variables (Gauthier, 2001). To assess statistical significance, we calculated p-values for each variable pair. Visualizations, including heatmaps, were deployed to clearly depict correlations, while scatter plots and stacked bar charts helped examine the linearity of relationships and the distribution of variables, respectively.

Qualitative responses from open-ended survey questions and transcripts of interactions with ChatGPT were subjected to thematic analysis to provide deeper insights into the qualitative aspects of participant experiences, uncovering underlying reasons, opinions, and contextual nuances that statistical methods alone could not reveal. This involved coding the responses systematically to identify recurring themes and patterns. Initial codes were generated inductively, directly from the data. Afterward, codes were grouped into potential themes, reviewed, and refined to ensure they accurately represented the data set.

This mixed-methods approach enriched the data analysis, enabling a more nuanced understanding of the complex phenomena of human-AI communication. By integrating quantitative and qualitative insights, the study could address both the 'what' and the 'why' of participant responses, thereby providing a richer and more comprehensive analysis of the collected data. This approach aligns well with the interdisciplinary nature of the research, bridging elements from communication theory, human-computer interaction, and cognitive science.

2.2. Results

Even with the constrained sample size, the empirical study provided a wealth of knowledge by analyzing key elements of the communication, task characteristics, and the effectiveness of human-AI communication in an academic research context. The results highlight several significant relationships that shed light on how to optimize the integration of AI tools. 12 variables representing human cognition, task, and communication characteristics were used to conduct the empirical study. We categorized the variables into Input Type Variables and Output Type for clarity and structured analysis given in Table 2. Input variables in the study primarily concern the initial conditions set by the participants or the initial setup of the experiment, which are directly connected to the interaction dynamics with the AI, ChatGPT. Output variables reflect the results of AI and participant interactions, highlighting the effectiveness of these interactions and the participant's responses. By dividing variables into 'Input' and 'Output' groups, we aim to understand better how initial conditions affect the results of human-AI interactions. This is important for creating more effective AI systems and enhancing the user experience in academic research environments.

Table 2

Definition of variables employed in the empirical study

Variable	**Definition of the variable**
Input Type Variables	
Comfort with AI	Participant’s self-reported comfort level with AI concepts and technologies, measured on a 5-point Likert scale, from “Very uncomfortable” to “Very comfortable”.
Contextual awareness	Participant’s self-reported contextual awareness on the voluntarily chosen research topic, measured on a 5-point Likert scale, where 1 is “Novice,” and 5 is “Expert”.
Clarity of expectations	The extent to which a participant expressed clear and realistic expectations about the experimental task with ChatGPT prior to interaction was assessed by researchers on a 3-point Likert scale: “Low”, “Medium”, and “High”. Three main factors were considered in the assessment of participants’ expectations in terms of clarity: 1) Specificity of the expectations, 2) The alignment of the expectations with ChatGPT capabilities, 3) The alignment of the expectations with the experiment goals.
Task difficulty	Participant's self-reported assessment of the research task's complexity, scaled on a 5-point Likert scale, from “Not demanding”, to “Extremely demanding”.
Information	Participant’s self-reported assessment of the relevance of ChatGPT's

relevance	responses to their research task, was measured on a 5-point Likert scale, from “Irrelevant”, to “Relevant”.
Output Type Variables	
Decoding quality	Participant's ability to accurately interpret and understand the information provided by ChatGPT. Evaluated by the research authors based on the research outline provided by participants, and participants’ self-reported evaluation of the relevancy and the clarity of the responses provided by ChatGPT, measured on a 3-point Likert scale, from “Low” to “High”.
Feedback frequency	The rate at which a participant modified their interactions with ChatGPT, either through providing explicit comments or revising their prompts in response to ChatGPT's output. The frequency was assessed by the researchers and categorize5d as “Frequently”, “Sometimes”, “Rarely”, or “Never”, where one feedback in every 3 prompts was considered as “Frequently”, in every 5 prompts considered as “Sometimes”, in every 7, or more prompts considered as “Rarely”. If there is no feedback at all during the interaction, then the feedback frequency is considered as “Never”.
ChatGPT effectiveness	Participant's self-reported assessment of ChatGPT's effectiveness in assisting with their research task, measured on a 5-point Likert scale, from “Not at all helpful”, to “Extremely helpful”.
User satisfaction	Participant's self-reported satisfaction level of their interaction with ChatGPT, assessed on a 5-point Likert scale, from “Very Dissatisfied”, to “Very Satisfied”.
Perspective taking	Participant's willingness to consider alternative perspectives based on ChatGPT's input. Their perspective taking was evaluated by the authors by grouping them into 3 categories: “Reserved”, “Moderate”, and “Open Perspective” groups.
Response verification	Whether the participant tried to verify the accuracy of the information provided by ChatGPT during the interaction. Marked by the authors as “Yes” or “No”, where “Yes” represents that the participant tried to verify the accuracy of the response provided by ChatGPT at least once, and “No” means that the participant never verified the accuracy of the response provided by ChatGPT.
AI introduction	The way the participant was introduced with the ChatGPT tool in the experiment instructions. 4 different introductions types were randomly distributed by the authors in the experiment instructions; 1) “You will be interacting with ChatGPT”, 2) “Your partner is ChatGPT”, 3) “ChatGPT will assist you”, 4) “Your tool will be ChatGPT”.

Source: Created by the authors based on Taylor, 1962, Canary & McPhee (2011)

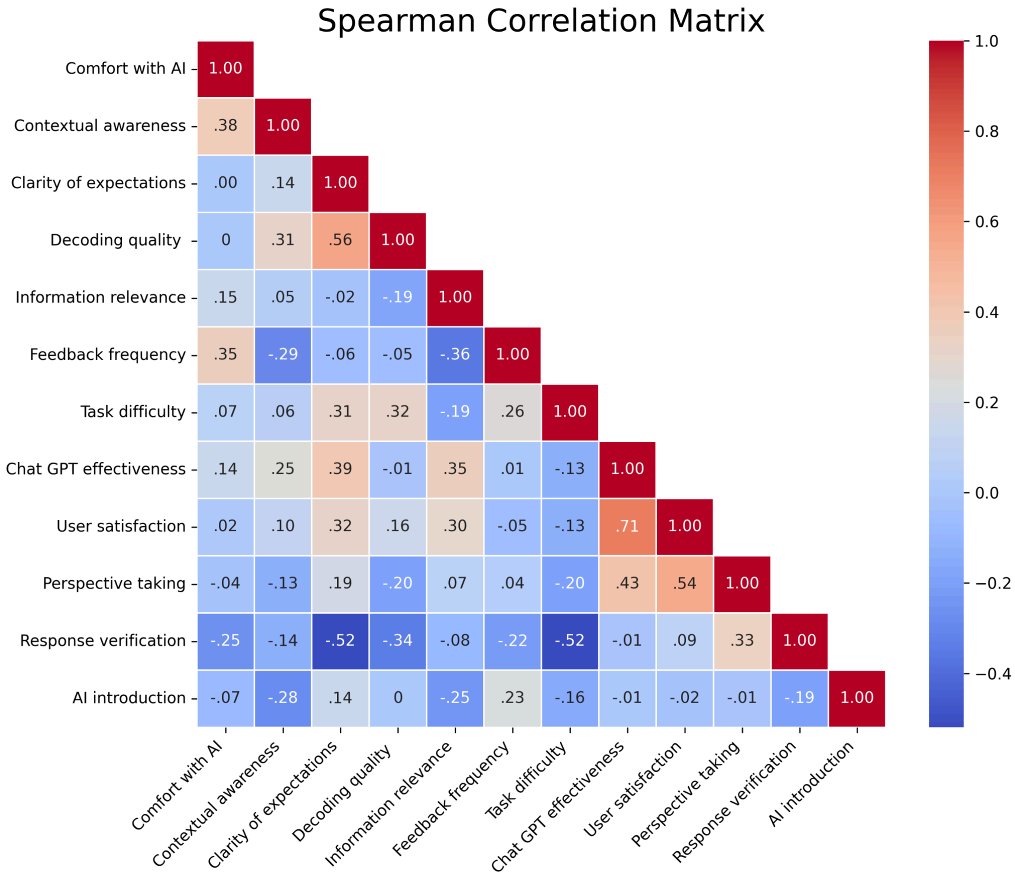
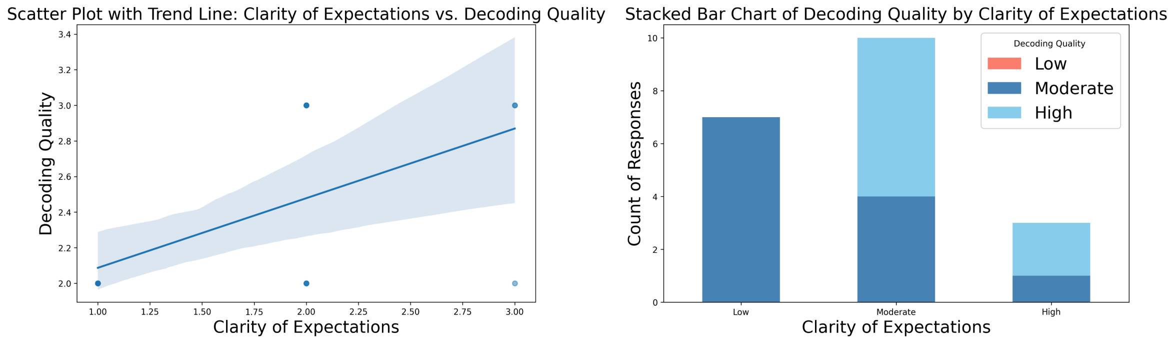


Figure 3. Heatmap of Spearman's rank correlation coefficient of variables, n=20
Source: Created by the authors based on study results

To analyze the data derived from interactions between humans and AI systems, the heatmap is presented in Figure 3 based on Spearman's rank correlation analysis on data collected from 20 study participants. It demonstrates several notable associations between variables, where the color intensity correlates with the strength of the relationship - red for a strong positive correlation and blue for a strong negative correlation. Furthermore, the heatmap employs stars to denote significance levels for three commonly used thresholds: a single star (*) indicates a p-value less than 0.05, two stars (**) signify a p-value less than 0.01, and three stars (***) mark a p-value less than 0.001. This visual representation assists in easily identifying the statistical significance of the correlations observed.

Scatter plots and stacked bar chart graphs were utilized to take a closer look at the relationships between moderately or highly correlated and statistically significant variables.

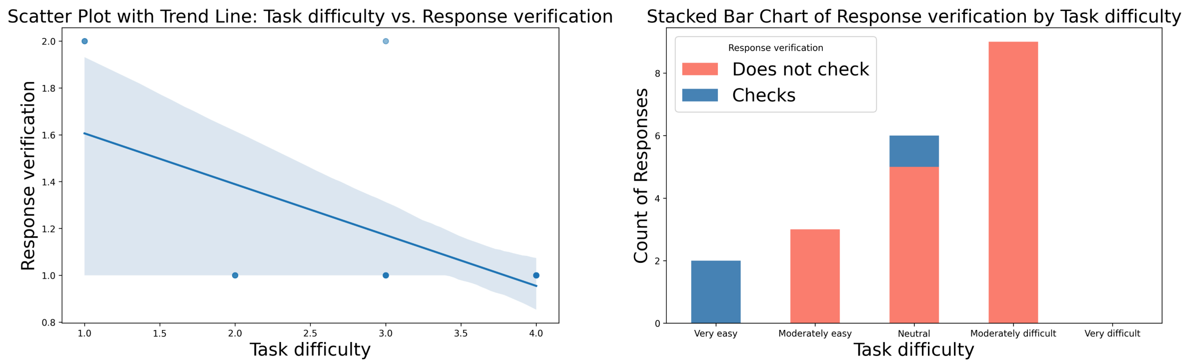


A **B**

Figure 4. (A) Relationship between Decoding quality and Clarity of expectations, n=20; *(B)* Distribution of Decoding Quality Ratings across Levels of Clarity of Expectations, Source: Created by the authors based on study results

Figure 4 (A) presents the scatter plot illustrating a positive association between Decoding quality and Clarity of expectations. This relationship is statistically significant (Spearman's $\rho = 0.56$, $p < 0.01$) and exhibits a moderate correlation strength. The upward-sloping trendline visually reinforces the finding that when users had clearer expectations of ChatGPT's output, they displayed a greater ability to interpret the information provided by ChatGPT. However, the presence of some scatter around the trendline suggests that while clarity is influential, other factors likely also contribute to the variation in clarity of expectations. The stacked bar chart in Figure 4 (B) provides further insights into the relationship between decoding quality and clarity of expectations. It highlights a shift towards higher decoding quality ratings as the clarity of expectation levels increases from "Low" to "High". This pattern aligns with the positive trend observed in the scatterplot. Notably, the proportion of 'Moderate' ratings of decoding quality decreases substantially, while the ratio of 'High' ratings becomes more prominent with participants' increasing clarity of expectations. Clarity of expectations, on the other hand has a moderately negative correlation with Response verification (Spearman's $\rho = -0.52$, which is statistically significant ($p < 0.02$)). This indicates that as clarity of expectations increases, users tend to engage less frequently in verifying the accuracy of ChatGPT's responses.

Interestingly, response verification shows another statistically significant, moderately negative correlation with task difficulty (Spearman's $\rho = -0.52$, $p < 0.02$). The scatter plot in Figure 5 (A) illustrates the relationship between task difficulty and response verification. Exhibiting a moderate correlation strength, the downward-sloping trendline implies that as Task difficulty increases, users tend to engage in the verification of ChatGPT's responses less frequently. However, some variability exists around the trendline, suggesting that other factors might also influence verification behavior. The stacked bar chart presented in Figure 5 (B) offers additional depth to this observed relationship—the distribution of response verification changes across different levels of task difficulty. The trend shows a higher proportion of verification of responses when the task difficulty is “Very easy”, accompanied by a decrease as the task difficulty increases. To sum up, the findings suggest that users might be less inclined to double-check ChatGPT's output when dealing with more difficult tasks. This pattern might reveal a complex interplay between user trust and the perceived difficulty of a task, deserving future research.



A **B**

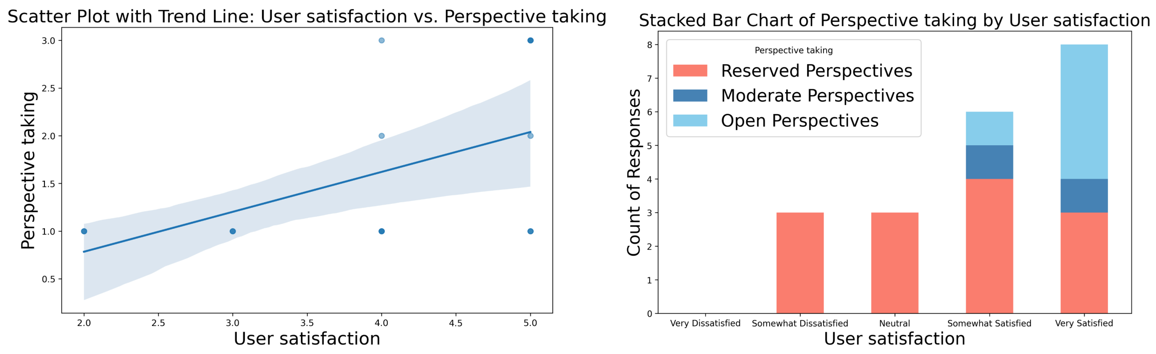
Figure 5. (A) Relationship between Task difficulty and Response verification, n=20; *(B)* Distribution of Response Verification Ratings across Levels of Task Difficulty

Source: Created by the authors based on study results

Based on the Spearman rank correlation heatmap, it is obvious that one of those variables affecting ChatGPT effectiveness is User satisfaction. A strong positive correlation between ChatGPT effectiveness and User satisfaction (Spearman's $\rho = 0.71$, $p < 0.001$) signifies that as perceived ChatGPT effectiveness increases, User satisfaction tends to increase correspondingly. A dramatic decrease in unsatisfied ratings and a substantial increase in “Somewhat Satisfied” and “Very Satisfied” ratings are observed as ChatGPT effectiveness improves. The positive correlation between perceived AI effectiveness and user satisfaction highlights the importance of developing robust, reliable AI tools that meet user needs and foster a positive experience.

User satisfaction, on its own turn, is moderately correlated with another variable employed in the empirical study - Perspective taking. The scatter plot presented in Figure 6 (A) reveals a positive association between these variables (Spearman's $\rho = 0.54$, $p < 0.01$).

The upward-sloping trendline suggests that higher User Satisfaction scores are generally associated with an increased tendency towards perspective-taking. However, some variability around the trendline implies that other factors might also influence this relationship. Figure 6 (B) provides additional context for understanding the relationship between User Satisfaction and perspective-taking. The proportions of different perspective-taking levels change across the bars representing different User Satisfaction categories. The chart shows a shift toward a greater proportion of higher Perspective-taking ratings in users expressing higher satisfaction levels.



A **B**

Figure 6. (A) Relationship between User satisfaction and Perspective taking, n=20;
(B) Distribution of Perspective taking Ratings across Levels of User Satisfaction
Source: Created by the authors based on study results

Lastly, and notably against our initial expectations, the contextual awareness of participants concerning their voluntarily chosen research topics did not show any statistically significant moderate or strong correlations with other variables. Despite this, Figure 4 and Figure 5 provide insightful scatter plots and stacked bar charts that delve deeper into the dynamics between specific input and output variables. Finally, although we aimed to measure the encoding quality of the participants, it was not possible to include it in our study as a variable. Since we were not able to get information about the thoughts of the users before they encode their messages, measuring the encoding quality variable was not feasible.

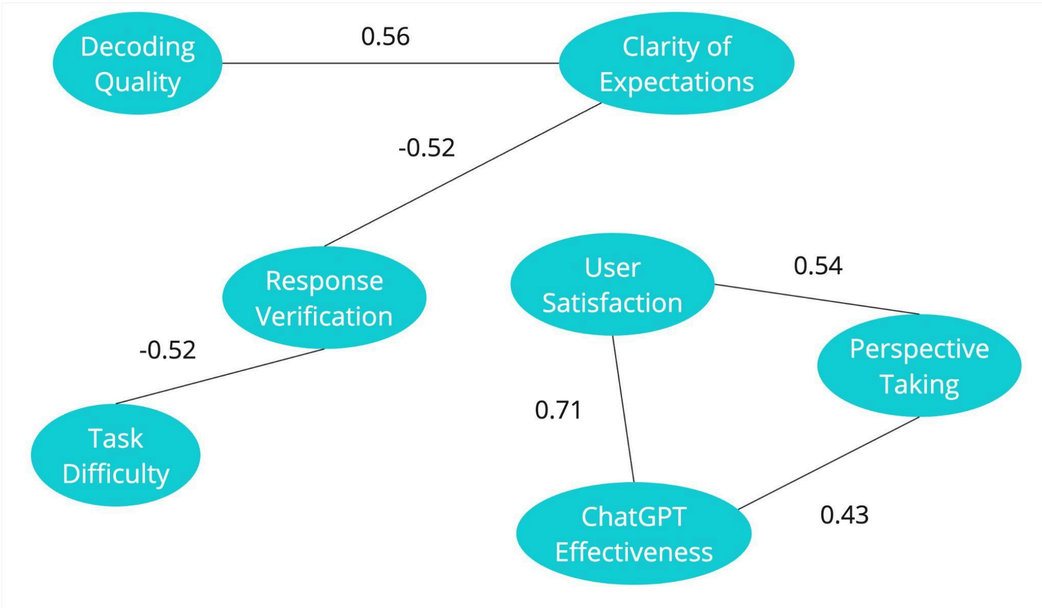


Figure 7. Correlation tree of the moderately ($\rho > 0.4$) and highly ($\rho > 0.6$) correlated variables. Here, ρ is Spearman's rank correlation coefficient given in *Figure 3*.
Source: Created by the authors based on study results

Our empirical study constructed a correlation tree in Figure 7 to visually represent the relationships and strength of correlations between key variables, as identified through our Spearman rank correlation analysis. This tree graphically delineates how each variable is linked to others, providing a clear visualization of our findings. Analysis of various variable clusters within the correlation tree suggests several factors potentially influencing their relationships. Firstly, clarity of expectations appears to be connected to the cognitive load involved in decoding and verifying responses. Similarly, increased task difficulty is expected to increase these cognitive demands. Additionally, a predisposition towards open-mindedness and adaptability seems to correlate with both user satisfaction and perceived ChatGPT effectiveness positively.

Key findings of our empirical study include:

- The connections between Clarity of Expectations, Response Verification, and Decoding Quality indicate that clear initial expectations about AI capabilities are associated with improved ability to interpret AI responses and are linked to variations in user engagement with these responses.

- The correlation of Task Difficulty and Response Verification behavior suggests that increased task complexity might lead to less frequent checks on AI outputs.
- The crucial role of perceived ChatGPT effectiveness in user satisfaction underscores the importance of AI performance in shaping user experiences, with more effective AI leading to higher satisfaction levels.
- The potential relationship between user satisfaction and perspective-taking indicates that satisfactory interactions with AI can encourage users to consider a broader range of perspectives, enriching the cognitive impacts of AI engagement.

The analysis underscores the importance of understanding user expectations, task attributes, and AI performance in facilitating successful human-AI collaboration within academic research. The positive correlation between the input variable clarity of expectations and the output variable decoding quality suggests that participants who begin their interaction with a clear understanding of AI capabilities are better equipped to interpret and utilize AI-generated insights accurately. This insight highlights the critical role of setting realistic user expectations before interaction, supporting the necessity for roles such as prompt engineers who specialize in optimizing human-AI communication. Conversely, the unexpected inverse relationship between the input variable task difficulty and the output variable response verification raises potential concerns regarding overconfidence or misplaced trust in AI, particularly in complex research scenarios. As tasks become more challenging, participants may rely too heavily on AI without sufficient verification, which can lead to errors or misinterpretations. This finding calls for enhanced AI design that supports adequate user engagement and critical assessment, ensuring that users remain active and effectively engage with AI outputs, regardless of task complexity. Lastly, but importantly, the positive correlation between two output variables, user satisfaction with perspective-taking, was observed. Participants with higher user satisfaction levels considered a broader range of perspectives comparatively, leading to better and more engaging human-AI interaction.

2.3. Discussion

2.3.1. Interpretation of Results and Implications

Our empirical research into human-AI communication has discovered crucial associations that shape the communication dynamics of these exchanges within academic research. The first research question of our study was the following: "*How are clarity of expectations and task difficulty connected to the encoding and decoding processes in human-AI communication?*" We observed that clarity of expectation wasn't merely a preliminary condition; rather, it structured the entire interaction framework. Participants who entered the study with clear, well-defined expectations about AI's capabilities could perceive the responses better, linking to the high decoding quality. Therefore, the participants with high decoding quality were not just passively interacting with ChatGPT, but they were actively leading the conversation, ensuring it remained relevant and productive. This echoes findings from recent studies, like those by Pataranutaporn, highlighting how expectations can significantly alter the user experience (Pataranutaporn et al., 2023). The precision in their expectations enabled participants to decode AI responses more effectively, leading to a richer, more critical engagement. However, regarding task difficulty, our findings did not show a statistically significant correlation with decoding quality, suggesting an area ripe for further study.

Our second research question was: "*What role does user engagement play in the effectiveness of human-AI communication in academic research settings?*". To answer this question, our analysis focused on the output variables and examined ChatGPT effectiveness and user satisfaction. Here, the strong positive correlation between how effective participants perceived the AI to be and their satisfaction levels was insightful. This finding aligns seamlessly with Chong's work, reinforcing the importance of designing AI tools that are not only technically proficient but also contextually aware to truly meet users' needs (Chong et al., 2022). Finally, our study led us to perspective-taking, an output variable, which shows a positive relationship with another output variable, user satisfaction. We found that participants who were more satisfied with the AI were also more open to considering diverse perspectives in their academic inquiries, leading to more engaging discussions. Consequently, these engaged users are more likely to utilize AI effectively, integrating it into their research processes as a supportive tool. Interestingly, this triangular relationship between perspective-taking, user satisfaction, and ChatGPT effectiveness can be observed as a cluster in the correlation tree presented in Figure 7. This clearly demonstrates how well-designed AI can encourage critical thinking and open-mindedness, which are essential qualities for academic research.

While interpreting the key findings of our empirical study to answer the research questions set, the exploration took us to the input variable task difficulty. Here, a notable pattern emerged. While one might expect that harder tasks drive people to double-check their work more diligently, our participants displayed the opposite trend. They were less vigilant in verifying the AI's output when faced with more complex problems. This unexpected twist suggests a possible overconfidence or a misplaced trust in AI's capabilities. This critical area needs further investigation to ensure AI tools are designed to encourage appropriate verification across all levels of task difficulty.

These insights lay foundational steps for future initiatives, emphasizing the critical roles of educators and academic institutions in shaping how students perceive and engage with AI. Incorporating AI literacy and critical thinking into educational curriculums will prepare students to not only use AI effectively but also critically evaluate and guide its applications. Moreover, for AI developers and policymakers, the clear message is the necessity for AI tools that challenge users intellectually and engage them deeply, ensuring AI is a genuine aid in academic endeavors. Ensuring AI tools that foster rigorous engagement and critical scrutiny is essential for advancing academic research and knowledge discovery.

2.3.3. Limitations and Future Research

One of the limitations we faced in our study was the small sample size. Due to limited resources, we could only involve twenty master's degree students from the University of Tartu. This small number might raise concerns about the generalizability of our findings. To address this limitation, we employed purposive sampling as our recruitment strategy. This method allowed us to carefully select participants who were actively engaged in academic research and likely to use AI tools. By choosing participants from diverse academic backgrounds, we ensured that our sample, although small, was representative of a broader range of perspectives and experiences within academic settings. Despite the small sample size, this approach allowed us to gather deep, meaningful insights into how different types of users perceive and interact with AI. Using purposive sampling ensured that each participant could provide valuable data specific to their experiences, thus enriching our understanding of human-AI interaction in academic research.

Another limitation was our reliance on self-reported data, which can sometimes introduce biases such as social desirability or self-selection bias. Participants might report behaviors or perceptions that are expected or socially acceptable rather than genuine feelings. To mitigate these potential biases, we designed the survey questions to be as neutral as possible to avoid leading questions that might sway the participants' responses. Additionally, we assured participants of anonymity and confidentiality to encourage them to be more honest and open in their responses. By taking these steps, we aimed to collect more accurate and reliable data, reflecting genuine user experiences and perceptions. The careful design of the survey and the assurance of confidentiality helped minimize the impact of biases, thus enhancing the trustworthiness of our findings.

The third limitation was the exclusive use of text-based interaction between participants and the AI (ChatGPT), which might need to fully capture the richness of human-AI communication that could occur in multimodal interactions (involving voice, video, etc.). Since our resources did not allow for a more complex setup involving multimodal interactions, we focused on designing a detailed and well-structured task environment. This setup helped ensure that the text-based interactions were comprehensive and allowed participants to express detailed thoughts and engage deeply with the AI. Despite the limitation of text-only communication, this focus enabled us to control and precisely analyze the interaction process. It allowed for a clearer interpretation of the cognitive processes involved in text-based human-AI communication. Additionally, our focus on text-based interactions reflects the common use of AI systems in academic and research environments today, making our findings both relevant and practical.

Our study predominantly utilized Taylor's communication theory to analyze human-AI interaction, which may have restricted our exploration to specific aspects of communication processes. This focus might limit the breadth of theoretical insights into the varied dimensions of how humans engage with AI. Although we concentrated on one primary theoretical perspective, we carefully selected Taylor's communication theory because of its relevance and proven applicability in understanding fundamental communication dynamics. This theory provided a robust framework for interpreting the interactions within our study, ensuring that our analysis was grounded in a well-established academic tradition. Focusing on a single theory allowed for a more in-depth exploration of specific communication aspects, such as message encoding and decoding, which are crucial for effective human-AI interaction. It provided a clear, structured lens through which to view our data, facilitating a focused analysis that yielded detailed insights into the cognitive processes involved in these interactions.

These limitations were carefully considered and addressed through strategic choices in our study design and methodology. By employing purposive sampling, ensuring neutrality in survey design, and focusing on detailed text-based tasks, we targeted to minimize the impact of these limitations. Though constrained in some areas, the study provides valuable insights that contribute to understanding and improving AI-enhanced communication tools in academic settings. These insights pave the way for future research to explore tons further, potentially with a larger sample size, more diverse backgrounds of participants, and richer interaction modalities.

Building on the findings and limitations of our current study, several areas warrant further investigation to enhance our understanding of human-AI interaction in academic research. Future research can extend and deepen the impact of this work in several key areas:

- Larger and More Diverse Samples - To address the limitation related to the small sample size in our study, future research should aim to involve a larger and more diverse group of participants. Expanding the participant pool across different universities and including a broader range of academic disciplines can help verify and generalize the findings. Such studies could also investigate cross-cultural perspectives on AI in academic research, exploring how cultural differences might influence user experiences and expectations of AI technologies.
- Incorporation of Multimodal Interactions - While our study was limited to text-based interactions, future research could explore multimodal interactions that include voice, gesture, and perhaps even emotional feedback. This would offer a more holistic view of the dynamics in human-AI communication and could uncover additional insights into how different modes of communication affect user satisfaction, efficiency, and the overall quality of interaction with AI.
- Comparative Studies Across Different AI Applications - Future studies might compare interactions with different types of AI platforms, not just ChatGPT. By including various AI technologies, researchers can identify specific features or capabilities that most significantly impact user experiences and outcomes. Such comparative studies could guide the development of more tailored AI tools that cater to the specific needs of academic researchers.

- Deeper Analysis of Cognitive and Communication Theories - Further research could also delve deeper into cognitive and communication theories to explore more nuanced aspects of human-AI interaction. For example, examining how specific communication theories apply to interactions with AI can reveal more about the underlying processes that govern user engagement and the interpretative strategies employed by humans when interacting with AI.
- Beyond Self-Report: Integrating Behavioral Metrics in AI Interaction Studies - Future studies might employ techniques such as eye-tracking, which can offer insights into participants' attention and engagement levels during interactions with AI systems. Similarly, physiological measurements, such as heart rate variability or galvanic skin response, could be used to gauge emotional and cognitive responses to AI interactions that participants might not fully disclose or even be aware of themselves. In addition to these methods, triangulation involving qualitative interviews and quantitative data could also be considered. This approach would allow researchers to validate self-reported data with actual behavior observations, providing a more rounded understanding of how users truly perceive and interact with AI.

In conclusion, our study contributes valuable insights into the dynamics of human-AI interaction within academic research, demonstrating the complex interplay between user expectations, task complexity, and AI effectiveness. By exploring these areas, future research can build on the groundwork laid by this thesis to further enhance our understanding of how AI can be effectively integrated into academic environments. These efforts will not only address the gaps identified but also expand the scope of research to ensure that AI tools are used to their full potential, enhancing both the productivity and the quality of academic research.

2.4. Conclusion

Throughout this thesis, we have investigated the interplay between cognitive factors and communication theory in enhancing human-AI communication. This exploration began with identifying a notable gap in the literature—the limited application of communication theory to studying human-AI interactions. This gap guided our research objectives, focusing on integrating communication elements such as encoding, decoding, feedback, and the influence of noise in communications.

Our findings emphasize the importance of clarity in expectations and task difficulty in the encoding and decoding processes within human-AI communications. Specifically, the study revealed that participants who had clear expectations of AI capabilities could better understand and utilize AI outputs effectively. This clarity facilitated more meaningful and productive interactions with AI tools, exemplified by using ChatGPT in our experiments. In addition, user engagement emerged as a pivotal factor in the effectiveness of human-AI communication. Engaged users who understood and could navigate the capabilities and limitations of AI experienced enhanced communication quality. This engagement was influenced significantly by the AI's ability to provide relevant and timely feedback, aligning closely with the users' research needs.

Linking back to the theoretical frameworks discussed in the initial chapters, our empirical results support the thesis that applying communication theory to human-AI interaction provides a robust foundation for understanding and improving these interactions. The theories of encoding and decoding were particularly relevant, as they helped explain how information is processed and understood in human-AI dialogues. The practical implications of our research are significant for academic settings, where AI can substantially enhance research efficiency and effectiveness. By integrating AI tools like ChatGPT that can support complex cognitive processes, educational institutions can foster an environment that enhances researchers' productivity and cognitive capabilities.

In conclusion, this thesis contributes to the broader discourse on artificial intelligence by providing new insights into human-AI interaction's cognitive and communicative dynamics. It highlights the need for clear communication and effective engagement strategies in designing and implementing AI systems. For future work, expanding the research to include a more extensive and more diverse sample, exploring different cultural contexts, and integrating multimodal communication could provide deeper insights and more generalizable findings. These efforts will further enrich our understanding and application of AI in various academic and practical contexts, bridging theoretical knowledge with real-world applications.

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Appendices

APPENDIX A

Instructions for the Experimental Task

Welcome to the Research Inquiry Experiment!

Objective:
This experiment aims to explore how you, as a master's degree student, can use ChatGPT to conduct preliminary research on a topic related to your field of study. This exercise is designed to simulate real-world academic research activities, where you might seek initial guidance on research topics, methodologies, or literature sources.

By participating in this experiment, you can increase your understanding of technology using AI for research. This opportunity prepares you for a world that values AI knowledge more and more and can play a role in making AI tools better for scholarly work.

Your participation in this study is entirely voluntary. If you choose to participate, please be aware that by continuing with the survey, you are providing consent for your data to be used for research purposes. However, at any point during the experiment, you have the option to withdraw without any consequences.

What You'll Do:

Before task:
You'll be asked to fill out a short survey about your background.
The link to the survey: https://forms.gle/DxkgGgv4GrNFSwiU7

Task With ChatGPT:

1. Select a Topic: Choose a topic of interest within your academic discipline. If you're unsure where to start, here are a few suggestions to get you thinking:
   - For Business students: "Emerging Technologies in Digital Marketing"
   - For IT students: "The Role of AI in Cybersecurity"
   - Feel free to pick any topic that excites you and is relevant to your studies!

2. For this task, you'll be interacting with ChatGPT. Through the ChatGPT interface provided, you're expected to inquire about a topic of your choice. By asking these questions and gaining insights into the topic, your aim should be to define a problem statement in your research area. Afterward, you should find out the research questions that address the problem. Finally, you should ask questions to discover key methodologies that could be used in the field.

3. Based on the information provided by ChatGPT, compose a brief outline of a potential research project (you must use your own interpretations). Your outline should include:
   - A clear problem statement.
   - A set of research questions you aim to answer.

- A proposed methodology for investigating these questions.

After the Task:

You'll be asked to fill out a short survey about your experience. This will include questions about how relevant and helpful you found ChatGPT's responses, the ease of use of the interface, and any challenges you experienced during the task.

The link to the survey: https://forms.gle/SDDRE2BLYZByMukS8

Why Your Participation Matters:

Your insights will contribute to our empirical study focusing on how users formulate questions, interpret AI responses, and how their background influences their interaction with AI to enable effective communication between humans and AI. This is an opportunity to influence the development of AI technologies to meet the needs of students like you better.

Please note!:)
Considerations:
- You will have one hour to complete the experiment.
- You should use a laptop to complete the experiment.
- After finishing the task, you will share the brief outline of your potential research project with us in the post-task survey.
- After finishing the task, you will share the link to the chat story you had with ChatGPT with us without any adjustments by using the interface's "Share" function in the post-task survey.
- We kindly ask you to give detailed responses to the open-ended questions in the survey. This will enable us to conduct a thorough analysis and achieve improved outcomes.
- The result of your task will not be shared or published with anyone else. The collected data is for researchers and will be kept undisclosed.

Ready to Start?

When ready, proceed to the ChatGPT interface [https://chat.openai.com/] and begin your research inquiry project. Remember, there are no right or wrong answers here; we're interested in your unique approach to using AI in your academic work.

Thank you for participating, and we look forward to seeing your innovative ideas and research outlines!
GO ON!:)

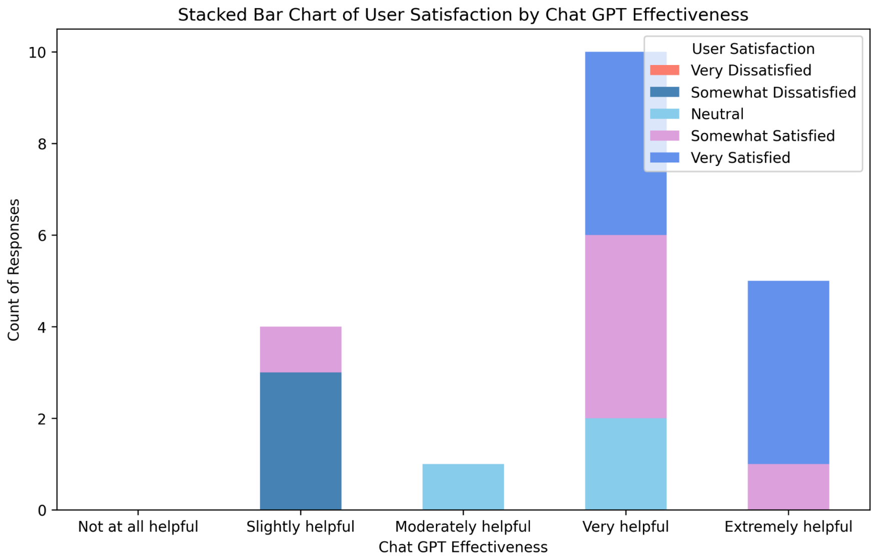
Source: Compiled by the authors

APPENDIX B

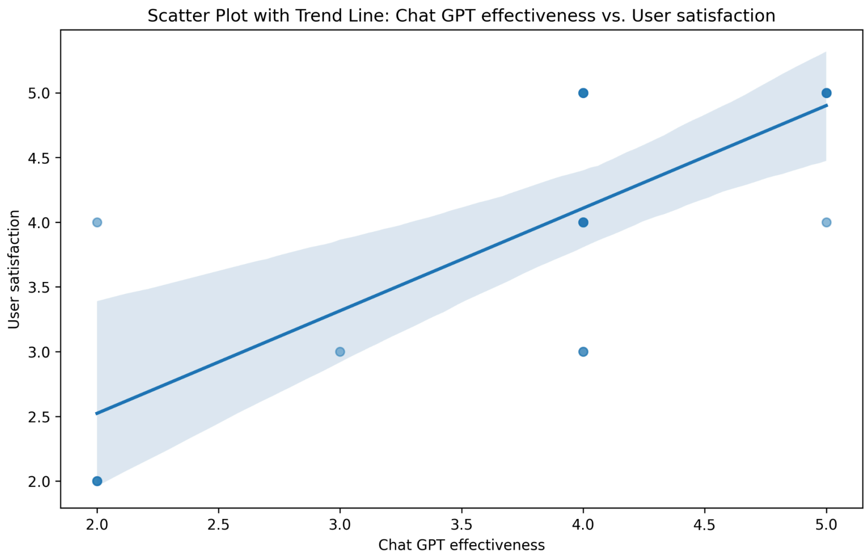
Collection and Analysis of Empirical Data

The data gathered from the experiment can be found here: Empirical study Table
The source code repository: https://github.com/gularmehman/thesis-empirical-study

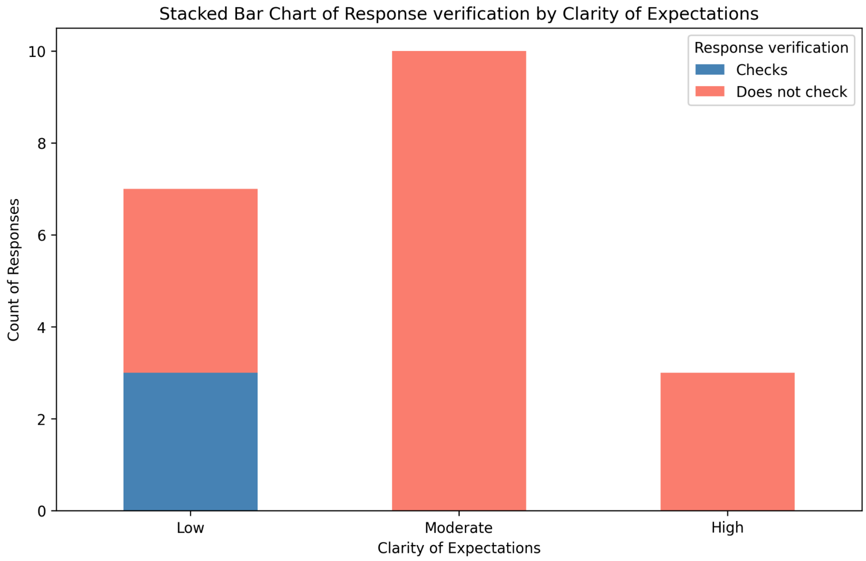
More Figures from the Results of the data analysis:



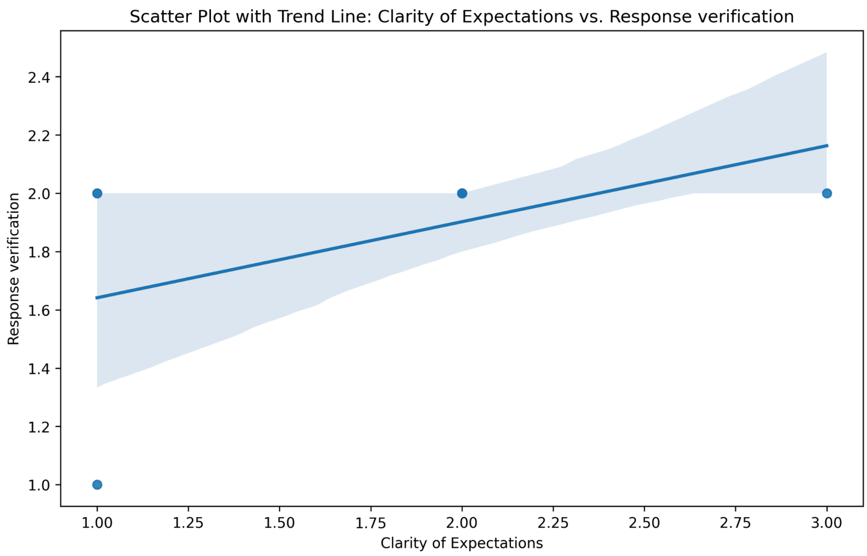
Relationship between User Satisfaction and ChatGPT Effectiveness
Source: Created by the authors based on study results



Distribution of User Satisfaction ratings across levels of ChatGPT Effectiveness
Source: Created by the authors based on study results



Relationship between Response Verification and Clarity of Expectations
Source: Created by the authors based on study results



Distribution of Response Verification ratings across levels of Clarity of Expectations
Source: Created by the authors based on study results

Resümee

KOMMUNIKATSIOONITEOORIA RAKENDAMINE TEHISARU-PÄRISARU VAHELISE SUHTLUSE HÕLBUSTAMISEKS AKADEEMILISES KONTEKSTIS

Gular Samadova, Orkhan Najiyev

Meie magistritöö keskendub kommunikatsiooniteooria rakendamisele inimese ja tehisintellekti (AI) vaheliste suhete parandamiseks, eriti akadeemilistes uurimisseadetes. Uuringu peamine eesmärk on integreerida oluliseimad suhtlemiselemente — kodeerimine, dekodeerimine, tagasiside ja müra — tõhustamaks omavahelist koostööd. Kasutasime segameetodilist lähenemist, kaasates eksperimentidesse ChatGPT ning magistriõppe tudengeid, et uurida, kuidas ootuste selgus ja kasutaja kaasatus mõjutavad suhtlusprotsessi AI-ga. Uuringu algfaasis viisime läbi põhjaliku ülevaate praegusest tehisintellekti maastikust, keskendudes tehisaru-pärisaru vahelisele suhtlusele. Tuvastasime olemasolevas kirjanduses olulise puuduse: kommunikatsiooniteooria põhjalik rakendamine tehisaru-pärisaru interaktsioonide uurimisel on sageli tähelepanuta jäetud. See ülevaade viitab vajadusele süsteemse lähenemise järele, mis arvestaks, kuidas põhilised suhtlemiselemendid saavad süsteemselt parandada AI integreerimist akadeemilistesse- ja uurimistegevustesse.

Meie magistritöö empiirilises osas kaasasime struktureeritud suhtlusesse ChatGPT-ga kakskümmend magistriõppe tudengit erinevatest akadeemilistest taustadest. Meie uuringu ülesehitus hõlmas enne ja pärast ülesannet läbiviidud küsitlusi, et koguda andmeid selliste muutujate kohta nagu ootuste selgus, ülesande raskus ja kasutaja rahulolu. Meie leiud näitasid, et selged ootused parandavad oluliselt AI kommunikatsiooni dekodeerimisprotsessi, võimaldades tõhusamaid suhtlusi. See teadmine on ülioluline, näidates, et hästi määratletud kasutajaootused enne AI-ga suhtlemist viivad paremate tulemusteni. Lisaks arutleb meie töö AI rolli üle uurimistöö tootlikkuse ja tõhususe suurendamisel, pooldades AI süsteemide arendamist, mis reageerivad ja kohanduvad kasutaja vajadustele. Argumendi kohaselt võib AI süsteemide kohandatavus oluliselt suurendada nende kasulikkust akadeemilistes seadetes, muutes need haridus- ja uurimisasutustele hädavajalikeks vahenditeks.

Meie uuring annab akadeemilisele diskursusele praktilisi lähenemisviise AI vahendite tõhusaks kasutamiseks haridus- ja uurimiskontekstides. Leiud rõhutavad vajadust integreerida kommunikatsiooniteooria AI arendusse, et tõhustada süsteemide funktsionaalsust ja kasutajasõbralikkust. See integratsioon aitab mitte ainult akadeemilises

kasutuses AI-d, vaid ka laiemates rakendustes, kus efektiivne tehisaru-pärisaru suhtlus on oluline. Kokkuvõttes on meie magistritöö oluline samm mõistmaks ja parandamaks tehisaru-pärisaru suhtluse dünaamikat akadeemilistes seadetes. See rõhutab selgete ootuste ja kasutaja kaasatuse tähtsust, pakkudes raamistikku, mida saab kasutada AI süsteemidega suhtlemise parandamiseks. Tuleviku uurimissuunad hõlmavad proovide suuruse laiendamist ja multimodaalse suhtluse uurimist, mis võiks pakkuda sügavamaid teadmisi tehisaru-pärisaru vaheliste kommunikatsiooni nüansside kohta. See uuring loob aluse edasiseks uurimiseks tehisaru-pärisaru suhtluse kognitiivsete ja suhtluslike aspektide osas, eesmärgiga täiustada ja laiendada AI integreerimist mitmesugustes akadeemilistes ja praktilistes rakendustes.

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