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Title

CORRELATION BETWEEN USER UNDERSTANDING AND SENSE OF AGENCY IN HUMAN-AI

Subtitle

A QUALITATIVE ANALYSIS OF AI'S IMPACT ON USER EXPERIENCE AND BEHAVIOUR IN WORK

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Tell us the story of your text in four short (tweet-length) statements:

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The key idea behind the thesis is to show how AI can change the work and behaviour of the users, forcing them to adapt to the new work ways and develop new skills for working with AI chatbots. The thesis illustrates in real-life settings how the collaboration between AI chatbots and users is affected by the users' own understanding and experiences with AI.

2) What motivated you to write about this?

The increasing adoption of AI in the workplace has been hyped due to the many benefits that AI chatbots bring, especially in terms of efficiency and cost reduction. However, I found that few addressed the impact of introducing AI chatbots to a work practice or discussed how to ensure the users had a positive work collaboration with a new AI. AI chatbots are to be used by users; as such, users drive the adoption of AI chatbots in companies.

3) Where or to whom might it be significant?

The findings of the thesis are relevant and significant to several actors. Companies can use the findings to adjust their strategy for AI adoption, ensuring a positive user experience. Designers and AI practitioners can use the findings to help enhance existing methods and practices for implementing AI in workplaces. The overall contribution is to push the AI development onto a more user-centric pathway, thereby implementing AI with the user's experience in focus.



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Brief abstract (300 words) in which the relation and relevance to STS is indicated

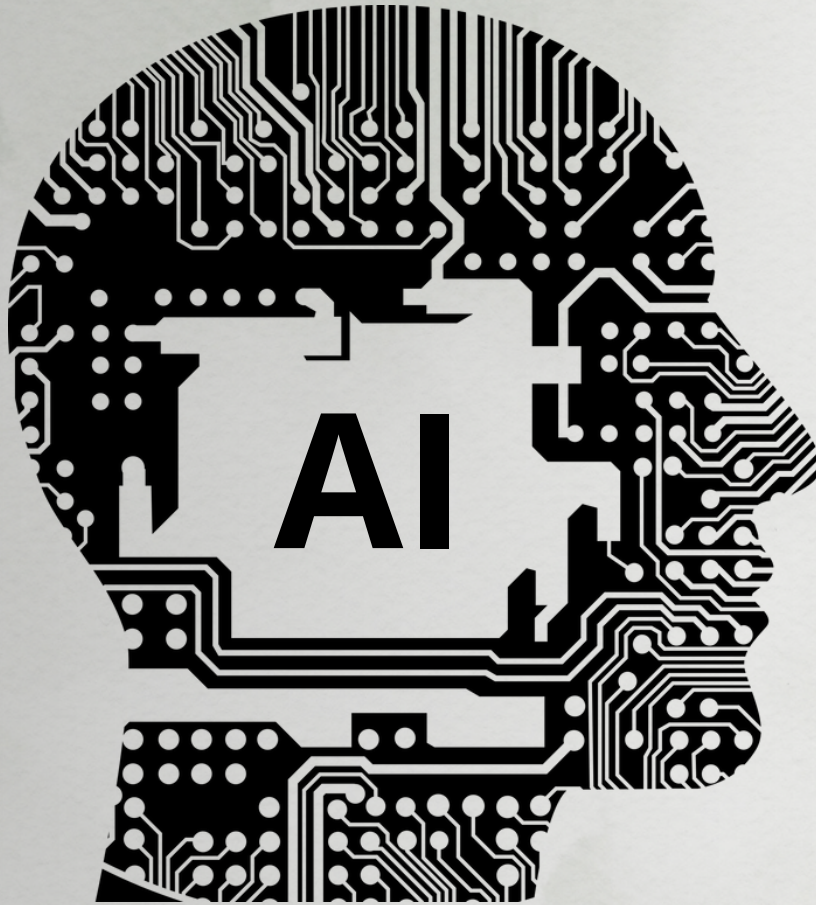
The thesis examines the evolving dynamics in human-AI collaboration in professional settings, focusing on how users construct understandings of AI assistants and how these understandings influence the users' perception of their agency. With the increasing embedding of AI assistants in the workplace, it has become crucial to explore their sociotechnical impact from a user-centric perspective. Specifically, the thesis will answer the research question: What understandings do users construct about how AI assistants work, and how do these understandings affect users' perceived agency? The dual focus emphasises users' mental models, encompassing their pre-existing understandings of AI and their perceived agency, which refers to their awareness of

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CORRELATION BETWEEN USER UNDERSTANDING AND SENSE OF AGENCY IN HUMAN-AI INTERACTIONS



**A QUALITATIVE ANALYSIS OF AI'S IMPACT
ON USER EXPERIENCE AND BEHAVIOUR IN
WORK SITUATIONS**

MASTER'S THESIS BY LAURA FRANSGAARD

Correlation between User Understanding and Sense of Agency in Human-AI Interactions

By

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Master's thesis, Spring semester 2025

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The thesis consists of 161.419 characters or 67,2 normal pages

May 28th, 2025

Abstract

In recent years, the rise of Generative AI innovation has made AI assistants a larger part of daily and work life for many users. The number of companies adopting AI assistants is increasing, despite a lack of understanding about the impact of AI as new technology on human-AI collaboration. Therefore, academic work must study human-AI interactions, especially in professional settings, to discover the influence of AI from a user-centric perspective. This master's thesis will investigate how AI affects users in human-AI collaboration by examining users' understandings and perceived agency in these collaborations. Specifically, the thesis will answer the research question: What understandings do users construct about how AI assistants work, and how do these understandings affect users' perceived agency? The dual focus emphasises users' mental models, encompassing their pre-existing understandings of AI and their perceived agency, which refers to their awareness of being in control.

The thesis adopted an interdisciplinary approach theoretically and methodologically. It used Taina Bucher's concept of algorithmic imaginaries, adapting it to contemporary times by integrating the psychological concept of the Sense of Agency. This framework analysed users' perceptions and behaviours in AI interactions by examining how they conceptualise AI and their sense of control in interactions. The framework was applied through an ethnographic and active participation methodology. By conducting interviews to explore user imaginaries and cognitive walkthroughs with a think-aloud protocol to observe agency in situ, the methodology focused on both what is articulated and what is enacted. The thesis was grounded in a case study of a newly implemented AI assistant at Kamstrup, a Danish energy company, providing an empirical setting.

The findings demonstrated how users constructed seven different AI imaginaries. The imaginaries entailed both the technical, interactional, and sensitive aspects of AI and shaped how users perceive and exercise their agency through their behaviour. The

correlation between imaginaries and agency is mutually shaping and dynamic in interactions with an AI assistant. (Mis)Alignment between the user's imaginary and the AI's capabilities can lead to exercised or strengthened agency and reactions from the user, such as frustration or satisfaction. Three factors were found to mediate the correlation: expectations, communication, and satisfaction. These factors are pathways to understanding the relationship between user imaginaries and exercised agency.

The thesis contributes to the growing field of human-AI interaction through empirical and theoretical insights into how users experience and adapt to AI. It highlights the importance of aligning users' mental models with the AI's capabilities in the design and implementation to enhance users' agency and human-AI collaboration. Future research could further explore the nuances of the correlation between imaginaries and agency in human-AI collaboration, such as the role of trust and longitudinal evolution.

Acknowledgements

I want to take this opportunity to thank the people who helped make this thesis possible.

Thank you to Kamstrup, especially Erin K. and Bjørn Carlsen, for helping me establish a collaboration and answering my thousands of questions.

Thank you to all the participants who agreed to participate in this project and for sharing their experiences and opinions.

I want to give a special thanks to my counsellor, Anders, for his support and guidance during this project. His help made me stand stronger.

Lastly, I would like to thank my closest ones for their unwavering support throughout the ups and downs. Thank you to my study group for providing a space to unload and discuss challenges and doubts.

Note to reader:

The second file, "Appendices," contains all appendices; they are not included in this paper for anonymity reasons.

I hope you will enjoy the product of my hard work; I wish you a happy reading.

Content

Abstract.....	2
1. Introduction	7
2. Theoretical Foundations.....	10
2.1. Interdisciplinary Research Position.....	11
2.2. Algorithmic Imaginaries	12
2.3. Sense of Agency	14
2.4. AI in the Workplace	16
3. The Case of Interest.....	18
3.1. The Users of Interest	19
3.2. The Object of Interest.....	20
4. Methodological Approach	22
4.1. Research design	23
4.2. Data Collection Methods.....	25
4.2.1 Pre-AI witnessing.....	25
4.2.2. Conversations of AI	27
4.3. Recruitment, Consent and Data Storage.....	33
4.5. Data analysis approach	34
4.5.1. Thematic coding	35
4.5.2. Two-cycle coding & Affinity Diagram	36
4.6. Ethical considerations.....	37
4.7. Limitations	40
4.8. Methodology summary.....	42
5. The Work before AI	42
6. Users' imaginaries of AI	45
6.1. The users' background and AI attitude	47
6.2. AI Imaginaries	49
6.2.1. Learning Entity	50

6.2.2. Data-driven System.....	51
6.2.3. Emotionless Agent	52
6.2.4. Personal Assistant	54
6.2.5. Super-computer	55
6.2.6. Communicative partner	56
6.2.7. Fallible Agent.....	58
6.2.8. Summary of imaginaries	60
7. Agency in HAIC	60
7.1. Overview of imaginaries.....	61
7.2. Impact of AI imaginaries on User Agency	62
7.2.1. Learn to trust.....	62
7.2.2. What and where is the data?	64
7.2.3. Question the lack of emotions.....	65
7.2.4. Personal potential.....	67
7.2.5. Super challenged	68
7.2.6. Communication clarity	70
7.2.7. It is okay to fail, but not that much.....	72
7.3. Alignment in Expectations, Satisfaction and Communication.....	74
7.3.1. Expectations	74
7.3.2. Communication.....	76
7.3.3. Satisfaction	77
7.3.4. Interpreting the Role of Expectations, Communication & Satisfaction	78
7.4. Summary of Agency in HAIC	80
8. Discussion of findings and contribution.....	81
8.1. Mutual shaping of imaginaries and SoA	81
8.2. Role of learning and experiences	82
8.3. Limitations of accessing inner thoughts	83
8.4. Practical and theoretical contributions	85
9. Concluding thoughts	87
10. References.....	89

1. Introduction

In 2022, OpenAI launched ChatGPT, demonstrating how a large language model chatbot can enhance human-like conversations through Artificial Intelligence (AI) (Jackson, 2023). ChatGPT is an AI assistant that uses Generative AI (GenAI) to produce content based on human input. GenAI enables AI assistants to simulate conversations via chat messages (Giordano et al., 2024). AI creates algorithms based on user input from chats, rather than using pre-programmed algorithms (Kang & Lou, 2022). Thus, GenAI involves systems that transform human input into generated responses in seconds (Giordano et al., 2024). The success of AI assistants hinges on easy interaction, leading to exponential growth in AI. 2023 marked the year people discovered GenAI, but 2024 became the year organisations began implementing AI assistants. A McKinsey survey indicates that the adoption rate of AI, such as GenAI, among organisations reached a new high of 72% in 2024 (Singla et al., 2024). AI has infiltrated the daily work lives of many organisations. This infiltration is also evident in users' adoption of AI assistants for work and leisure purposes, supported by ChatGPT's user base with about 5.19 billion monthly visits, making it the ninth most visited website globally (*Chatgpt.Com Website Traffic, Ranking, Analytics [February 2025]*, n.d.). AI has become an integral part in several aspects of life for many users.

Studying AI has become increasingly imperative as the technology is becoming widely adopted. The rise of AI assistants in the workplace introduces new challenges for users, who must navigate interactions with opaque and impenetrable AI systems (Shin, 2023). Users face a new daily life where interactions with AI are becoming increasingly unavoidable (Giordano et al., 2024). These interactions are complicated, as AI assistants are designed to communicate in a human-like manner but are built as opaque black-box technologies (Shin, 2023). Users are thus in an unfavourable position, making it difficult to understand and trust the AI (Böckle et al., 2021). User adoption of AI assistants is also

hindered by AI systems failing to meet user expectations, and the design prioritising business needs over user needs (Janssen et al., 2021). An imbalance between user expectations and AI capabilities can lead to user frustration and collaboration issues, causing users to view the chatbot as ineffective and hindering the adoption (Janssen et al., 2021). The challenges highlight an uncertainty of how users are affected by AI assistants and how they navigate these interactions.

Literature suggests investigating AI's effects through users' understanding of it. Users' pre-existing perceptions, attitudes, and expectations influence their interactions with AI assistants (Ngo, 2022; Schellewald, 2022). In other words, a mental model shapes behaviour and entails personal conceptions of external experiences (Rook, 2013). Users' mental models, brought into AI interactions, frame their understanding of the system (Bucher, 2017; Schellewald, 2022; Ngo & Krämer, 2022; Mehrotra et al., 2023; Molina & Sundar, 2024). Their past experiences and knowledge of algorithms underpin initial opinions and decisions with AI technologies (Wang, 2023, p. 6). Previous encounters with AI create a memory framework for new ones. Users construct mental models by feeling algorithms are present, even without technical knowledge (Schellewald, 2022). The mental models closely relate to users' expectations of and navigation with black-box AI assistants. The impact of AI can be examined through mental models framing users' interactions with the AI.

Another way to study AI's impact is by examining the agency between the user and the AI. When interacting with an AI assistant, users engage with an algorithmic system that exercises social power and agency (Beer, 2017). AI assistants perform as a system of data-driven agency and intentionality (Borsci et al., 2024). Just like AI, users also exercise their agency and intentionality in interactions. The result is a human-AI interaction with two actors, each influencing the other's agency. Users continually attempt to understand algorithmic processes through their mental models to identify how they can exercise agency (Kang & Lou, 2022). When users exercise their agency, it manifests in small acts of

engagement contextualised to the given AI, intending to maintain or gain control over their experience (Kapsch, 2022). Agency is a contextual phenomenon that depends on both the user and the AI assistant. Agency is important for AI adoption (Araujo et al., 2020), as it enables users to feel in control of their experiences and be aligned with the AI's agency.

Both users' mental models and agency with AI are keys to examining AI's impact on user experiences. Mental models shape user interactions and influence feelings of agency. A correlation between users' mental models and their perceived agency is possible in interactions with AI assistants. This project will examine the impact of AI on user experiences through users' mental models, perceived agency, and their correlation. Specifically, the project will seek to answer the following research question:

What understandings do users construct about how AI assistants work, and how do these understandings affect users' perceived agency in their interactions and behaviours with an AI assistant?

As such, this project will explore how users understand AI systems, how they experience agency and how these two perspectives might correlate. This will be achieved through a methodology and theoretical foundation derived from an interdisciplinary research position. The thesis will employ an ethnographic and active participant methodology, primarily consisting of semi-structured interviews and a cognitive walkthrough, combined with a think-aloud approach. Interviews investigate users' articulated mental models of AI, examining how users understand an AI assistant and AI in general. A cognitive walkthrough assesses how users interact with an AI assistant, considering the agency they exercise and the form of collaboration they experience. The research question will also be answered through a theoretical foundation that draws upon Taina Bucher's *algorithmic imaginaries*, a theory on mental models of algorithmic systems (2017). The theory is adapted to modern-day scenarios with AI assistants by applying *Sense of Agency* (SoA), a psychological concept. The updated theory will examine how

users perceive AI chatbot algorithms, focusing on their experience and agency during interactions.

The methodology and theory are applied to a case study to support user-centric AI in the workplace by emphasising the link between users' understanding and experienced agency. Through a case study in Kamstrup, a Danish energy company, the project will identify how employees understand and navigate interactions with a newly implemented AI assistant. Findings will support the implementation of AI in the workplace, promoting user-centric AI and enhancing human-AI collaboration (HAIC).

This thesis paper will begin with outlining the theoretical foundation (Section 2), the case study under investigation (Section 3), and the applied methodology (Section 4). Hereafter, the thesis will present the relevant findings on users' current work practices (Section 5), their constructed AI imaginaries (Section 6), and the correlation between the imaginaries and SoA in HAIC (Section 7). The thesis will discuss the nuances and impact of the findings (Section 8). Lastly, the thesis concludes with a summary of the study's key results and contributions (Section 9).

2. Theoretical Foundations

This chapter outlines the thesis's research position and proposed theoretical framework. The collected literature is utilised to position the project, demonstrate its relevance, and elucidate theoretical concepts. The literature has been collected through a *narrative review*. The review method employs a holistic perspective to identify primary studies on the problem of interest through an ad hoc approach (ScienceDirect, 2025). The author has combined literature from past assignments and projects, along with an informal literature search focused on the keywords: *algorithmic imaginaries*, *AI*, *user understanding*, *sense of agency*, and *chatbots*. The search was conducted on the AU Library, Google Scholar, ACM and Scopus. The databases were chosen based on the author's

experience with them and their relevance to the field of Information Studies and Algorithmic Studies. The narrative review aimed to evaluate primary studies and narrow the project's position within other research fields. Based on the narrative review, the author can situate the project's theory, research position and scope with existing research. This chapter demonstrates the project's relevance, scope and basis of understanding.

The chapter begins by describing the project's interdisciplinary research position. Subsequently, it explains the theories of algorithmic imaginaries and SoA. The chapter concludes with an account of AI assistants in the workplace, explaining why the phenomenon is important to investigate.

2.1. Interdisciplinary Research Position

Due to the advancing innovation and development of AI, the impact of AI assistants is expanding to various aspects of users' daily lives. Therefore, it is increasingly crucial to reassess current theories on the user-AI relationship. To accomplish this, the project takes an interdisciplinary research position, drawing on the strengths of three distinct areas: Critical Algorithmic Studies, Human-AI Interaction and Media Studies.

This thesis explores daily human-AI interactions through Critical Algorithmic Studies, examining AI systems as socio-technical constructions that impact users' lives (Seaver, 2017). Sociotechnical constructions are knowledge assemblages that do not require expertise to understand (Gillespie, 2016). This perspective enables AI assistants to be viewed as agentic social constructs, rather than merely passive technology. Critical Algorithmic Studies emphasise humanistic and social scientific approaches to algorithms (Seaver, 2017), expanding the concept to include AI technologies based on algorithmic systems. Therefore, a foothold in this field helps to analyse AI assistants as sociotechnical constructs and algorithmic systems through a critical user perspective.

The study draws on the field of Human-AI Interaction (HAX), examining communication and collaboration between humans and AI to create user-friendly systems.

It integrates design, psychology, and computer science (Interaction Design Foundation - IxDF, 2023), providing a nuanced view of human-AI relationships. The Human-AI collaboration (HAIC) framework promotes successful partnerships between users and AI (Fragiadakis et al., 2024), aiming to facilitate efficient collaboration. This project aligns its perspective on human-AI relations with HAX and HAIC, using the term HAIC for scenarios where human and AI collaborate.

Lastly, the theoretical framework is based on Media Studies, particularly Taina Bucher's concept of algorithmic imaginaries (2017). The aim is to draw upon a media studies theory and adapt it to the current situation in which AI systems enter new areas of daily life beyond social media. The aim is achieved by applying a psychological aspect of agency to algorithmic imaginaries. This thesis develops a theoretical framework to understand the impact of AI on users' lives, with a focus on the correlation between user understanding and interactions with AI.

This project adopts an interdisciplinary approach, integrating Critical Algorithmic Studies, HAX, and Media Studies. This combination enables a nuanced investigation of human-AI relations, focusing on user understanding and agency. By bridging these fields, the project establishes a strong intersectional position to examine AI's impact on daily life. The interdisciplinary position underpins the project's exploration of how users perceive AI assistants through imaginaries.

2.2. Algorithmic Imaginaries

The attitudes users hold towards algorithmic systems closely relate to how users engage with algorithms (Ngo, 2022). For example, users with a critical negative attitude are likelier to engage in avoidance behaviour, refraining from using certain technologies. Users' pre-existing understanding, attitudes, and expectations influence their interactional situation with algorithms (Ngo, 2022). Wang (2023) also demonstrated how users' algorithmic acceptance influences their perceptions of AI-moderation, specifically the

filtering and categorisation of user content to remove misinformation. Algorithmic acceptance refers to “the extent to which they accept algorithmic decisions over human ones” (2023, p. 3). A high level of acceptance makes users more perceptible to AI moderation. Algorithmic acceptance as an attitude stems from users’ constructed mental models of AI. The constructed mental models are ways of investigating users’ attitudes toward AI systems’ workings, including their algorithmic acceptance, and how they might interact with the AI (Böckle et al., 2021).

Mental models encapsulate user understanding of AI as algorithmic systems and can also be conceptualised in what Taina Bucher calls “algorithmic imaginaries” (2017). Algorithmic imaginaries encompass how users understand algorithms and their workings. Taina Bucher defines algorithmic imaginaries as “ways of thinking about what algorithms are, what they should be, how they function and what these imaginations in turn make possible” (2017, p.40). Imaginaries are the mental models that users construct due to their awareness of algorithms, but they are incomplete understandings of algorithms’ inner workings. By following a phenomenological paradigm of perceiving things despite not having direct access, algorithmic imaginaries allow one to perceive algorithmic systems through the experiences and emotions of the users. The theory of algorithmic imaginaries has proven efficient in identifying users’ constructed understandings of algorithmic workings in daily, mundane situations (Bucher, 2017; Schellewald, 2022; Ngo & Krämer, 2022).

While algorithmic imaginaries are prominent in media studies, other theoretical concepts have also explored similar lines of thinking. Eslami et al. (2016) conceptualised *folk theories* as “non-professional perspectives via first-hand experience and social interactions” (p. 2372), the theories users construct to try and understand algorithmic curation in news feeds. The concept focuses on mapping out the different theories users construct but fails to consider the correlation between theories and action strategies (Schellewald, 2022). In contrast, algorithmic imaginaries seek to address this by focusing

on in-situ experiences between users and algorithms. Schellewald proposed the concept of *stories of algorithms*, which encapsulates how ordinary users express and distribute their lived experiences with algorithms to other users. Schellewald's theory relates closely to *algorithmic gossip*, as described by Bishop (2019), in which YouTube vloggers share knowledge about algorithmic processes through loose gossip. Both focus on the informal discourses shared between ordinary users. While both Bishop and Schellewald draw upon Bucher's algorithmic imaginary, they fail to consider the aspect of agency as capable of shaping and being shaped by the users' experiences. Lastly, Molina & Sundar (2024) proposed that heuristics serve as "*mental shortcuts that influence their perceptions of AI*" (p. 3639); users who perceive AI as more capable and objective than humans apply a positive machine heuristic, and vice versa for a negative machine heuristic. While this theory considers the context of interaction and users' differences in their perception of AI, it still cannot evaluate the effect of heuristics on users' experienced agency. Although Molina and Sundar noted that a user's perceived control over a system may influence the applied heuristic, it is not the focus of their study. In summary, several studies demonstrate the significance of users' mental models in their interactions with algorithmic systems. However, few have yet to fully explore the agentic aspect of human-AI interactions; therefore, this thesis proposes an extension of the original algorithmic imaginary theory through the psychological concept of *Sense of Agency*.

2.3. Sense of Agency

This study will acclimate algorithmic imaginaries to current situations by combining them with the psychological concept of Sense of Agency (SoA), thereby considering users' existing understanding and adding depth through agency. SoA is "the subjective awareness of initiating, executing and controlling one's volitional actions in the world" (Pagliari et al., 2022, p.3), meaning an individual's conscious awareness of their behaviour and actions. The concept emphasises users' self-awareness and self-control (Moore, 2016).

With the rise of more autonomous AI applications, concerns about privacy, transparency, and human control have grown, creating stronger tension between machine agency and human agency (Sundar, 2020). The tension is complicated by traditions in AI research that prioritise high automation at the expense of human control (Shneiderman, 2020). Suppose humans are excluded from the development and process of AI; they will be unable to take control when automation fails, thereby creating an overreliance on machines in tasks where humans still play a role (Yu et al., 2024). Therefore, ensuring human control in interactions with AI assistants is crucial for developing AI systems that humans will readily adopt and use. If humans feel in control of the AI they are using and understand the possible consequences of the AI, they are more likely to embrace it (Shneiderman, 2020). As such, SoA can be seen as the primary driver of human behaviour and is thus pivotal in establishing human control in human-AI interactions. SoA can be measured in various ways (Yu et al., 2024).

Two layers of agency can be used to investigate SoA in human-AI interactions. *Body agency* refers to the SoA people use to control their bodies, and *external agency* refers to people's feelings of control over external events (Yu et al., 2024). This study focuses solely on the external agency and the extent to which people feel they have control over the outcome provided by an AI assistant. This study focuses on external agency, as it is deemed the most feasible and achievable approach. External agency can be measured through explicit measures where the participant is asked to report their experiences directly (Yu et al., 2024). Other explicit measures could include visual feedback to confuse the outcome of actions or to prompt participants to judge the feedback outcome (Moore, 2016). The emotional report was chosen as the measurement since the author lacks access or the capability to program visual feedback into an AI assistant. In addition to explicit measurements, implicit measurements, entailing measuring cognitive mechanisms, were also an option, but they fell outside the author's capabilities and focus. Following Yu et al. and Moore's suggestions, the SoA is measured as the external agency through explicit

measures of subjective judgment reports. However, no choice of measurement is free from limitations.

This form of agency measurement is not without its complications, as Pagliari et al. (2022) argue; the black-box effects of automation complicate SoA, as they limit transparency and hinder effortless understanding of a system's workings. SoA is influenced by system transparency, attention resources, operational performance, and human perception. These factors intertwine and complicate the analysis of SoA (Yu et al., 2024). Therefore, SoA should be considered a contextual agency influenced by individuals and the AI.

The pervasive infiltration of AI assistants into users' daily lives underscores the importance of considering the aspect of agency (Wagner, 2019). Combining algorithmic imaginaries with SoA is thus hypothesised to strengthen each other. One adds depth and new aspects to the other, and vice versa. The theoretical foundation will encompass the impact of AI on users' daily work experiences through a correlation between mental models and contextual agency. The framework is designed for application in cases where users interact with AI at the workplace.

2.4. AI in the Workplace

With new technological advancements in AI, including GenAI tools such as ChatGPT and Co-pilot, AI assistants have gained enormous popularity among a large user base. The market for such AI chatbots is estimated to be \$102.29 billion by 2026, driven by increasing user interest, which has also led to a surge in scholarly work on chatbots (Janssen et al., 2021). The popularity of AI assistants can be attributed to their usability and easy interaction format, as users can write their requests, known as prompts, and receive an instant response (Giordano et al., 2024). With the numerous capabilities of AI assistants, integrating them into human work practices has become almost inevitable. AI offers several benefits in work-related use cases, including lower business costs, faster processes,

and enhanced managerial decision-making, which has led to its adoption by numerous industries (Westphal et al., 2023). The high adoption rate means users may need to collaborate with AI assistants as a new part of their work practice.

According to Fragiadakis et al. (2024), the introduction of GenAI has led to a new form of collaboration between humans and AI. The roles between humans and machines are becoming more blurred, as AI develop in capabilities. There are different forms of HAIC, but Westphal et al. (2023) sum up the idea to “In human-AI collaboration, the AI system and the user interact, share their prior knowledge, and ideally decide unanimously” (p. 2). However, collaboration can span a spectrum from fully automated AI decision-making to primarily human decision-making. The ideal situation is thus a sweet spot between the two extremes. AI enhances human decision-making and benefits the users in their work practices (Westphal, 2023). The benefits of AI are hence reliant on the form of HAIC. The collaboration is unlikely to be successful if humans experience no increased efficiency in routine tasks.

The unsuccessful adoption of HAIC can be attributed to the challenges of implementing AI assistants in the workplace. AI chatbots fail when they cannot meet users’ expectations, specifically regarding user trust, privacy, ease of use, and usefulness (Janssen et al., 2017). Bias significantly impacts HAIC, particularly in terms of automation bias and algorithmic aversion. Automation bias refers to the preference for automated recommendations over human ones, whereas algorithmic aversion is the preference for human decisions despite the accuracy of AI’s automated suggestions (Westphal et al., 2023). Users’ bias can affect their attitude towards and adoption of HAIC. In addition, AI adaptation in the workplace may increase productivity, but it can also change the skills required to perform the job. For example, to apply AI to work situations, users must be able to prompt and evaluate AI performance. This set of skills may not have been required beforehand, and therefore, users may not be adequately equipped to collaborate with AI

(Giordano et al., 2024). AI adoption in the workplace is thus challenged by unmet user expectations, bias, and the need for new skill sets, which can complicate the HAIC.

Overall, AI is rapidly entering the workplace across several industries; however, the successful adaptation and implementation of AI depend on human expectations and attitudes. The users' perception, knowledge, and capability to use AI are pivotal factors in achieving an effective HAIC at the workplace. One case of a newly established HAIC has been of interest to this thesis project.

3. The Case of Interest

This study employs a theoretical framework through a case study approach, highlighting its contextual and qualitative benefits. A case study examines a single phenomenon in detail, focusing on the observed setting, including individuals, technologies, and relations. This method enables researchers to sample social relations and test theories within a limited scope (Silverman, 2013).

The case in this thesis centres on a Danish energy company, called Kamstrup, which sells water, electricity, and district heating meters. The author developed a professional relationship with Kamstrup through an earlier internship, which enabled the establishment of a thesis collaboration. During the internship, the author learned about a new AI project: an internal product knowledge AI Assistant set for implementation in Spring 2025. This AI assistant, referred to as the Case AI (CAI), is Kamstrup's first internal knowledge assistant, providing a novel opportunity to examine its impact on the users' work.

The CAI was implemented in Kamstrup's customer support and product management teams. The case was chosen to understand how the CAI would impact users' experiences collaborating with an AI assistant. This case enabled the author to observe and

compare the teams' practices and experiences with the CAI. The argumentation for choosing this specific case was based on the following reasons:

1. A limited, specific user group
2. An organisation with resources to support the project
3. An organisation inexperienced with AI assistant implementation
4. A newly implemented AI assistant, based on a GPT model

Points 1 and 2 became known during the author's internship. The author chose the case to ensure a clear user group, specifically the teams receiving CAI within the organisation. This enabled the author to restrict her project and scope to these users, focusing on their work practices and experiences of having a specific AI assistant implemented. Point 2 was essential to ensure the author had enough interview participants and available contact persons to communicate with and to gain knowledge of the CAI.

Points 3 and 4 became clear to the author through informal, preliminary, and ad hoc interviews and observations of Kamstrup and the CAI. These ad hoc interviews and observations are not considered part of the formal data collection, but a pre-research activity to determine if the CAI case was feasible and appropriate. Through observing meetings and speaking with project management, it became apparent that Kamstrup was unfamiliar with implementing AI assistants. As such, Kamstrup became a company of interest for its new move to adopt AI into its work practices. Additionally, the CAI, as an off-the-shelf product, exemplified how companies can adapt new technology to meet their specific needs. It was found that Kamstrup focused on a simple yet effective AI model at a reasonable price, which was capable of meeting both users' and management's expectations.

3.1. The Users of Interest

The case focused on the team members of three customer support teams and one product management team, who had an AI assistant implemented in their work. The

organisation has three distinct business areas, each with its own customer support and product management teams. The three customer support teams vary in size and are responsible for their respective customer groups. The product management team is closely related to and collaborates with one of the customer support teams.

One team was involved in the CAI project in December, while the other two were added later. All the teams received a “How to Use GenAI” course from the CAI project manager as an introduction to using GenAI chatbots in the workplace. The course was not specific to the CAI, but rather a more general introduction. Thus, users of CAI may have limited or no experience with GenAI; therefore, Kamstrup provided a general introduction to AI. A HAIC has not been characteristic of the users' work practice before, and thus, it is an interesting case for a newly established HAIC.

3.2. The Object of Interest

Based on initial conversations with project management and documentation on the CAI, the author gained a basic understanding of the CAI. The documentation will not be disclosed due to a lack of consent to share. The author reviewed it during informal investigations, which are not considered part of the formal data collection. This section provides a basic understanding of CAI.

The CAI was built by an external vendor, a Danish tech company specialising in off-the-shelf AI solutions for other companies. CAI is based on the multimodal GPT-4omni model, designed for enterprise usage, as it enables custom AI templates. The CAI operates within Kamstrup's own Azure environment to ensure the proper security of company secrets and information. The CAI has a regular GenAI chatbot interface, which is illustrated below.

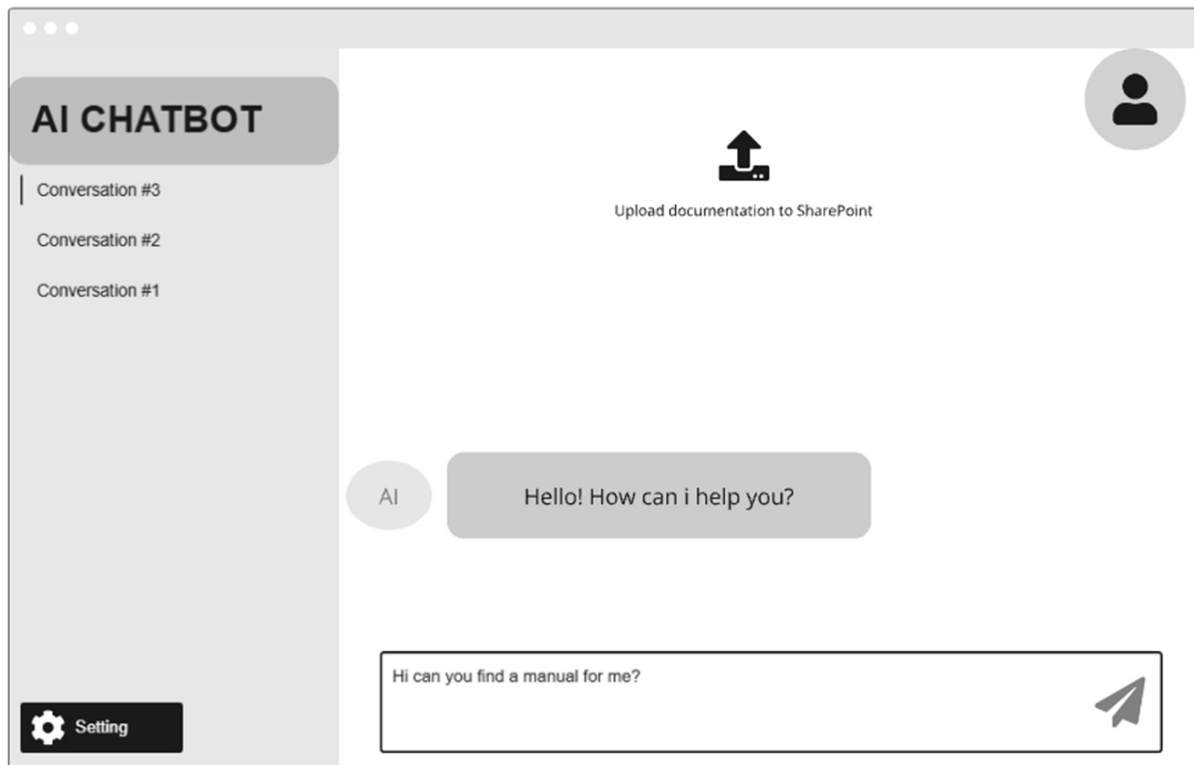


Image 1 – Illustration of the CAI chat interface.

Although the interface resembles other chatbots, such as ChatGPT or Co-pilot, the CAI's knowledge and capabilities are limited. CAI is a specific GenAI designed for particular work situations within large organisations. It accesses a SharePoint folder within the organisation's network, containing indexed manuals and documentation for a specific product group. Users can upload documents to this folder directly or through the chat. Unlike ChatGPT or Co-pilot, the CAI is specifically designed to answer questions about this documentation or related topics. Only users with access can use CAI, provided they have an organisational account, which limits the number of users but ensures data security and privacy. Chats with CAI are deleted after 30 days, permanently removing data unless the chat is reactivated. According to a developer from the CAI vendor, it does not iteratively learn or save chats due to data protection protocols.

In sum, the case of interest involved a newly implemented AI assistant in Kamstrup designed for the customer support and product management teams. The case was chosen

due to its novelty, convenience, the author's relationship with the organisation, and the necessary resources available to make the project feasible. The case offered a limited scope for investigating the impact of AI assistants on a user group, making it suitable for examination through an ethnographic and design-inspired methodology.

4. Methodological Approach

This chapter outlines the methodology, introducing the overarching approach and detailing the research methods' purpose, procedure, and ethical considerations.

The general methodological approach characterising this study was the *phronetic iterative* approach formulated by Tracy (2020). The author has consistently compared existing theories and research questions to emergent qualitative findings. This approach enabled a parallel and alternating work practice, where the author switched between reading data and applying existing theories. This has benefited the project by enabling the author to consider all forms of emerging insights and constantly adapt the research to the empirical data. The phronetic iterative approach relates closely to the *grounded theory* method, a systematic, inductive and comparative approach (Bryant & Charmaz, 2008). Both approaches move back and forth between emerging analysis and empirical data. Tracy (2020) noted that, despite its popularity, grounded theory stems from a post-positivistic and realist approach. The iterative phronetic approach emphasises how data extends theory rather than tying meaning exclusively to emergent data. Thus, the focus shifts from "grounded" to "iterative" for a more reflexive data analysis (Tracy, 2020). The author supported Tracy's argument and conducted the thesis using a phronetic iterative approach. A constant comparison enabled the author to adapt and examine the correlation between user understanding of AI and experienced agency in both applied theory and emergent data.

To understand how users perceive AI assistants and their agency, it was essential to investigate both words and actions. The project investigated users' algorithmic imaginaries and compared them to their SoA in interactions with CAI. Algorithmic imaginaries focus on the situations where users and algorithms interact (Bucher, 2021). Therefore, the theory would best be applied through an in-situ participation methodology to capture behaviours and interactions. This methodology helped users reflect on their felt tensions and agency with AI (Kapsch, 2022). Thus, the study employed a ethnographic and active participatory methodology the promote in-situ reflection. The following section outlines the overall research design.

4.1. Research design

The project employed engaging participatory methods through two primary data collection methods, which were analysed in a qualitative and phronetic iterative manner. The following overview depicts the applied research activities, their purpose, and the corresponding analysis approach.

Activity	Method	Focus	Analysis
Pre-AI witnessing	Participant witnessing	Understanding the existing work practices.	Thematic coding & Interpretation
Conversations of AI	Semi-structured interview, Cognitive Walkthrough	Understanding the participants' imaginaries and perceived agency in interactions with CAI.	Two-cycle coding, Affinity diagram

Table 1 – Overview of Research Methods and Analysis Approaches.

The *Pre-AI Witnessing* activity employed an ethnographic observational method to understand users' daily work prior to the implementation of the CAI. This was done to better assess the CAI's impact on users' work by understanding their backgrounds and

work tasks. The *Conversations of AI* research activity aimed to delve deeper into users' impressions of AI and their interactions with the CAI. The research activity used two data collection methods: semi-structured interviews and cognitive walkthroughs. Semi-structured interviews examined users' understanding of a specific AI chatbot and AI in general. The cognitive walkthrough, combined with a think-aloud approach, involved users solving typical work-related problems with the CAI while articulating their experiences to the author. This method helped to understand how users' imaginaries influence their perceived agency when interacting with AI assistants. As previously mentioned, this method focused on fostering active participation in the users through in-situ reflections and reactions to collaborating with CAI. Due to the thesis's user-centric focus, the methodology also incorporated ethnographic methods.

The research employed an ethnographic approach, examining the phenomenon holistically and descriptively, with a focus on the participants' perspectives (Blomberg & Burrell, 2012). Ethnographic research methods encompass the broader context of a phenomenon by examining events and activities within their natural environment. As Blomberg and Burrell argued, "By striving to describe and understand how people operate in and construe their everyday 'realities,' ethnography can provide useful frameworks and roadmaps to guide the design of 'people-centred' solutions" (p. 1029, 2021). Ethnography often entails collecting observational and interview data and is characterised by a flexible and contextually evolving process (Creswell, 2009). Ethnography is thus beneficial in evaluating technology from a human-centred, everyday perspective to understand the lived realities of the users. Therefore, this project employed ethnographic methodology to focus on the lived experiences and contextually dependent everyday realities. Specifically, ethnographic interviews and observation were used for the data collection.

4.2. Data Collection Methods

The project employed active participatory and ethnographic methods to collect data on users' existing work practices, imaginaries of AI, and their SoA in HAIC. The study used the following research methods for data collection:

- In-field participant witnessing
- Interviews and cognitive walkthroughs with a think-aloud approach

The data collection methods were used in the two primary research activities, Pre-AI witnessing and Conversations of AI (cf. Table 1). This section will describe how the research activities applied the collection methods and for what purpose.

4.2.1 Pre-AI witnessing

Participant witnessing, or observations, involves complete immersion in the situation (Tracy, 2020). In the Pre-AI witnessing research activity, the author engaged in the users' work environment, utilising all her senses for a deeper understanding. This approach went beyond mere sight, allowing her to observe not only spoken exchanges but also unspoken meanings and tacit knowledge. As Tracy noted, "Participant witnessing allows researchers to examine participants' actions as a means to understanding their values" (2020, p. 78), highlighting how tacit knowledge can clarify users' tensions or values. Many mundane issues become apparent in real-time space, often unnoticed by the user group. Participant witnessing guided the author in understanding the research phenomenon, despite her initial unfamiliarity with the users' practices. It also served as a crucial entry point into the user group.

The team manager introduced users to the author, verifying her authenticity and increasing their comfort in interacting with her. The author observed one employee at work or sat in the workspace to witness the work environment. The image below

illustrates the author's position in the office: the green circle represents her, while the yellow circles depict the team members.

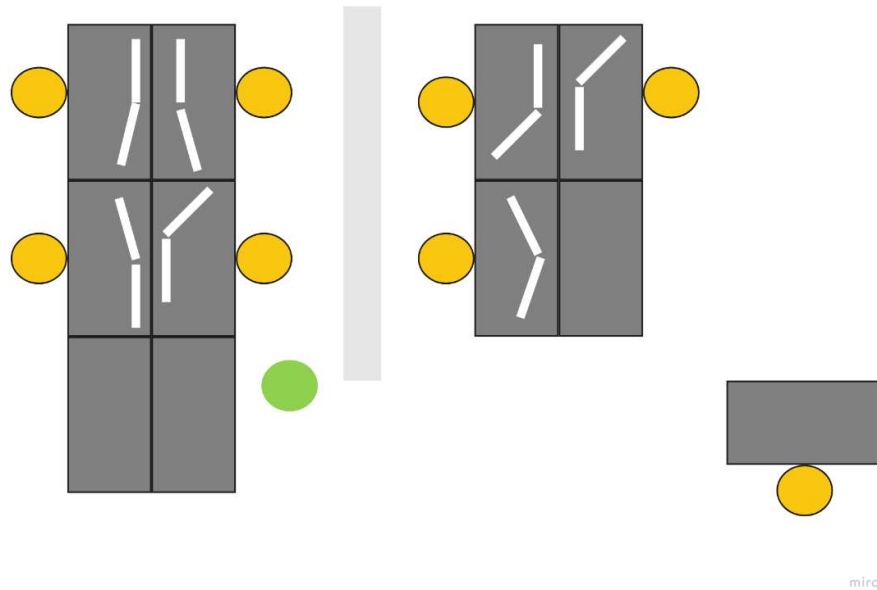


Image 2 - Illustration of the author's position (green) with the team members (yellow) in witnessing sessions.

The author participated in formal meetings as well as informal gatherings, such as breakfast or coffee runs. Thus, the author opened various spaces to observe the user's conversations and behaviours across the whole work spectrum.

The author carried only a notebook and a pencil to minimise barriers and take notes discreetly. The raw notes from the witnessing were transcribed into field notes within 36 hours to record the impressions and understanding clearly. Following Tracy (2020), the author created detailed descriptions of the context, enabling her to re-enter the space weeks later. The analysis method of the field notes is explained in section 4.5.

Participant witnessing explored the users' reality but prioritised their comfort and privacy. During the activity, the author may have witnessed unrelated events or overheard private conversations. The author refrained from sharing gossip or personal information not relevant to this project and conducted ethical witnessing, respecting users' rights to discuss their lives at work. The author ensured that all witnessed users signed an

informed consent form before witnessing began; this is detailed in Section 4.3, "Participant Recruitment and Consent." Pre-AI witnessing facilitated the author's invitation for users to participate in the next research activity, Conversations of AI.

4.2.2. Conversations of AI

The Pre-AI witnessing laid the foundation for conducting one-on-one sessions with participants to understand their constructed imaginaries and experienced agency in interactions with the CAI. The Conversation of AI sessions were structured in two parts, Part 1(P1) and Part 2 (P2):

P1: Semi-structured interviews on user understandings and experiences of AI

P2: Cognitive walkthrough with a think-aloud protocol with the CAI

Both parts were completed in the same session, within a 1-1.5-hour timeframe, and in the participants' native language, Danish. P1 focused on the users' articulated imaginaries of AI and their experiences with using AI in both work and leisure contexts. P2 entailed an in-situ, reflexive activity where participants solved tasks in collaboration with CAI and were prompted to reflect on their experience.

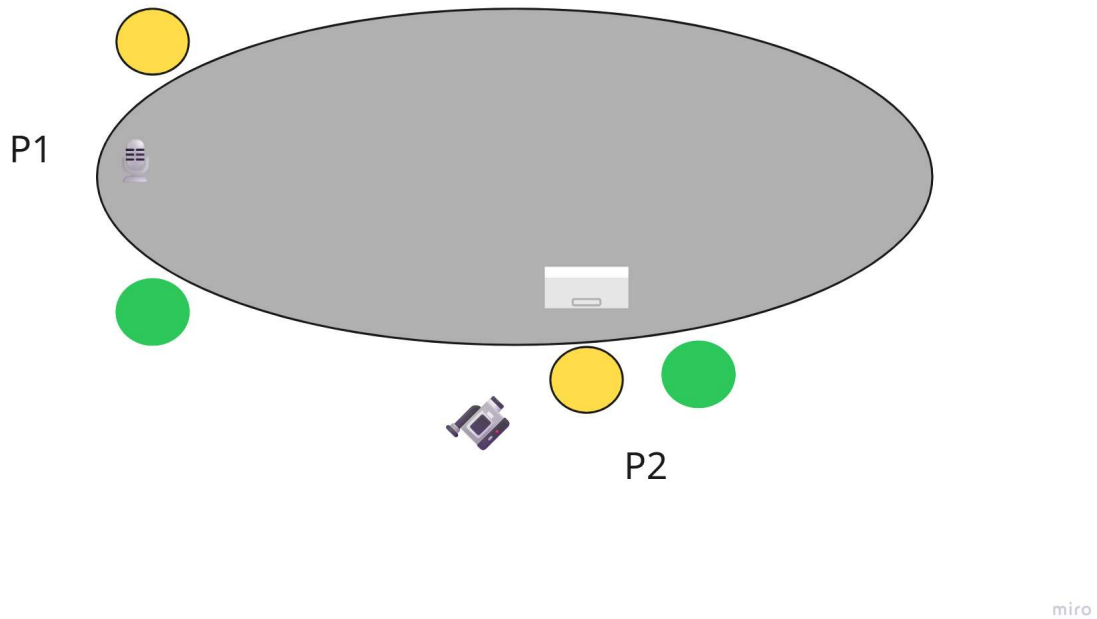


Image 3, illustration of the setup during Conversations of AI. Green marks the author, yellow marks the participant.

P1 and P2 occurred in a meeting room at the organisation's office to help participants return to work comfortably. The setup is illustrated in Image 3. P1 took place at one end of the table, allowing the author and participant to sit across each other and converse calmly. Coffee, water, and cookies were provided as a token of appreciation for the participants. P1 was audio recorded, as the spoken word was prioritised over facial expressions, which helped participants feel comfortable being recorded. P2 took place on the other side of the table, with the participant in a chair in front of a computer and the author beside them. A video camera positioned behind the stool captured only the computer screen, along with audio and finger movements. This was to ensure the author could revisit the situations to investigate tacit knowledge, chat interactions and tone of voice. The following sections will explain P1 and P2, focusing on procedure and considerations.

P1 semi-structured Interviews

P1 initiated a conversation about users' experiences, knowledge, and thoughts on AI assistants. This part employed semi-structured interviews, allowing for flexibility in following up on participant responses. Conducted in accordance with Tracy's (2020) guidelines, the interviews began with introductory questions and gradually became more specific. An interview guide, based on Tracy (2020), was used to facilitate the conversation and help the author pose relevant questions. It included an introduction, interview questions linked to research questions, and a task protocol for P2 (Appendix 1). The introduction explained the purpose and format of the interview, participants' rights, and encouraged the use of examples. The interview questions were tailored to keep the conversation focused on project interests without directly posing research questions, ensuring clarity and a formal yet neutral tone. The interview guide addressed these key points:

- The participants' articulated mental models of AI
- The participants' experiences with AI
- The participants' impression of AI in the workplace
- The participants' approach to AI

The guide began with an introductory question to familiarise the author with the participant's personality, work experience, and educational background. It then featured typology questions (Tracy, 2022), asking participants to explain their understanding of AI, chatbots, and CAI. This was to distinguish whether participants see these technologies as distinct or collectively. Additionally, the guide included action and behaviour questions (Tracy, 2020) about the participant's AI usage in both work and leisure contexts. Otherwise, the posed questions were adapted depending on the participants' responses and anecdotes.

During the interview, the author practised active listening. This involved concentrating, understanding, remembering, and sometimes responding (Tracy, 2020). The goal was to engage participants and show genuine interest in their opinions. The author asked follow-up questions to clarify or deepen her understanding of the participants' experiences. As Tracy (2020) noted, interviewing requires more than just asking questions; it involves presence and behaviour.

All interviews were audio-recorded and transcribed using Microsoft Word's dictate function or GoodTape (About – Good Tape, n.d.), and were thoroughly checked by the author. She listened to the recordings while reviewing the transcripts to ensure accurate documentation of participants' points and experiences. The Danish transcripts are provided in the Appendices, a second file provided at submission. The transcripts were then analysed qualitatively, as will be detailed in section 4.5. The second part of the data collection in Conversations of AI entailed the P2 cognitive walkthrough.

P2 Cognitive Walkthrough

Kapsch (2022) underpinned P2 activity, asserting that user engagement with algorithms leads to reflections on agency and knowledge. An active participatory approach links users' agency with reflections on AI. Combining cognitive walkthroughs with a think-aloud protocol achieved this reflexivity. Cognitive walkthroughs assess interfaces by guiding users through task flows (Sharp, 2019). Initially focused on usability (Bland, 2024), cognitive walkthroughs served as a qualitative digital research method to explore relationships between technical interfaces and contextual elements (Cavagnuolo et al., 2021). This perspective on the CAI highlights it as a sociotechnical artefact shaped by user interaction. To focus on user reactions and experiences with CAI, the author implemented a think-aloud protocol to elicit reflections.

Implementing a think-aloud protocol ensured that users reflected on their tasks and expectations in comparison to the AI's responses. This approach involved the author

prompting users to continuously articulate their thoughts and reactions (Tracy, 2020). For instance, when users wrote to the CAI, the author would prompt, “Why did you ask that question?” and “What do you hope to get as an answer?” as examples. The think-aloud protocol helped understand users’ thought processes and provided empirical data on their thinking (Charters, 2003). The prompting questions focused on users’ agency, emotional reactions, and expectations of the CAI. Combining cognitive walkthrough and think-aloud methods created an activity that allowed users to explore technology while reflecting on their thought processes. In summary, this combined method centred on users’ self-awareness and experienced agency when interacting with the CAI.

In the P2, a set of tasks in the interview guide directed the walkthrough (Appendix 1). The tasks were constructed by asking the CAI, “What are the typical questions a Customer Support team member would ask you about Kamstrup meters?”. As such, the tasks were based on what the CAI had indexed as everyday tasks for the user group, meaning what the CAI was designed for. Based on the CAI suggestions, the author selected five questions and rewrote them into feasible tasks. The tasks were formulated based on the insights of the users’ work from the Pre-AI witnessing. The author added a sixth task, which would go beyond the product-related scope. The tasks are seen in the following table.

Task title	Task objective
Task 1: Find product information	Find information about a specific product, incl. functionalities, specifications and application.
Task 2: Data analysis	Get information about which software can be used to retrieve data from a product
Task 3: Error finding and support	Get assistance in solving a problem with a product.
Task 4: False connection	Get the CAI to confirm/deny specifications for a product.
Task 5: Installation and setup	Get guidance on how to install and set up a product correctly.
Task 6: Irrelevant topic	Get a beginner's guide to baking cinnamon buns.

Table 2, an overview of the task posed in Cognitive walkthrough.

The task protocol consisted of six distinct tasks. The task was tailored to the participants' work, such as their designated product responsibilities. For instance, in Task 1, participants would find information on a product they manage. Tasks 1 to 3 emphasised the specificity of the CAI, allowing diverse prompts and assessing response value. Task 4 was based on preliminary discussions with the project group, addressing issues with false answers, prompting critical reflection on the CAI's potentially inaccurate responses. Task 5 simulated a scenario in which participants guided a customer while interacting with CAI. Task 6, a "joker," encouraged participants to ask an unrelated question, highlighting the CAI's limitations and ending the session on a good note. Task 6 was emphasised less than the previous five tasks if time was tight.

The questions were product-related and thus highly technical. The author had no prior knowledge of the technical aspects, so she was unable to assess the tasks beforehand. As the goal of P2 tasks was not to determine whether participants could complete them but to examine how they managed them, therefore the preliminary assessment was

deemed unnecessary. The author reevaluated the tasks after the first interview and found them appropriate and feasible based on the participant's experience.

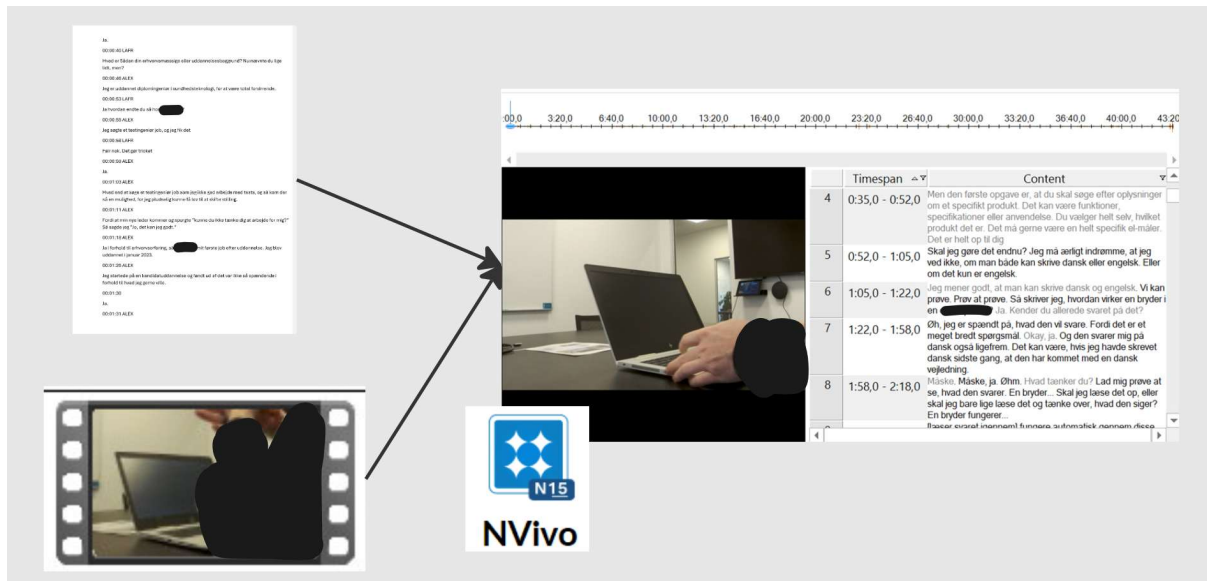


Image 4, illustration of the process of combining transcripts and videos.

P2 yielded videos as data, which the author transcribed using Microsoft Word's dictate function. The transcripts were synchronised to the videos using NVivo, an online qualitative analysis tool (NVivo, n.d.). The author aligned the timestamps in the transcript with the videos (Image 4), thereby preparing the data for coding and analysis, which will be elaborated on in section 4.5. The data collection was heavily dependent on participant recruitment, consent, and the appropriate storage of data for analysis.

4.3. Recruitment, Consent and Data Storage

Recruitment of participants and scheduling of witnessing sessions were facilitated by contacting the team manager. The manager introduced the author to the team members, and from there, the author made appointments with those team members who were willing to participate in witnessing sessions and interviews for Conversations of AI. The author communicated directly with the five participants for Conversations of AI, as she had an agreement with Kamstrup that granted her access to online accounts similar to

those of other employees. Upon agreement, the author scheduled a calendar meeting and booked a meeting room for Conversations of AI.

Every participant voluntarily signed an informed consent form, following the template provided by Aarhus University (Appendix 2). This was to ensure that participants comprehended the study's risks and benefits. When handing out the forms, the author explained how the participants' answers and personal data would be used, stored and deleted after project submission. Following Tracy's (2020) guidelines, participants were informed of their rights to decline participation and to have their data deleted or withdrawn from the study. The informed consent form was designed to protect the participants' rights and ensure that the study adhered to the Institutional Review Boards (IRBs) ethical standards. The potential ethical risks and limitations of this study are elaborated in Section 4.6 of the discussion. As per the informed consent, the processing and storing of the participant's answers and information followed an ethical and secure procedure.

All audio and video recordings and transcripts were stored on Aarhus University's OneDrive, ensuring safe and secure storage. Local copies were also stored on the author's computer, in case of emergencies or technical errors that might result in the loss of the online copies. In the informed consent, and orally expressed to the participants, the author promised and planned to erase all copies after the project had ended. The data was stored to ensure secure protection for the author to work with the data during the analysis.

4.5. Data analysis approach

The general iterative phronetic approach (cf. 4.1) was also applied to data analysis. By comparing new findings with existing theories, the author adapted the project based on her discoveries. The two research activities, Pre-AI Witnessing and Conversations of AI, were analysed differently, as shown in Table 1. Both analysis methods were suitable for the qualitative data and were chosen to highlight the strengths of the data format.

Hereafter, the analysis approaches will be explained in detail, including their purpose, procedure, and outcomes.

4.5.1. Thematic coding

An open-minded, data-driven thematic coding approach analysed the field notes from pre-AI witnessing. The field notes are not attached due to the inclusion of personal information; therefore, only the analysis findings are included, as they adequately capture the author's insights.

A theme illuminates a person's experiences by linking text sections from empirical data, such as field notes. Thematic coding involves systematically analysing the text through intensive reading (Gibbs, 2007). The data-driven thematic coding focused on understanding the situation without imposing a pre-existing theory (Gibbs, 2007, p. 45). In data-driven coding, the data determines the themes. The author coded larger text sections ad hoc and gathered general themes from various sections (Kvale, 1994), condensing meaning and assigning thematic categories. As field notes are subjective interpretations and not exact reflections, they served as the author's view of the world (Gibbs, 2007). They were designed to immerse the author in participants' work life, helping create an interview guide for Conversations of AI (cf. 4.2.2). The following image shows the coding process of field notes into themes.

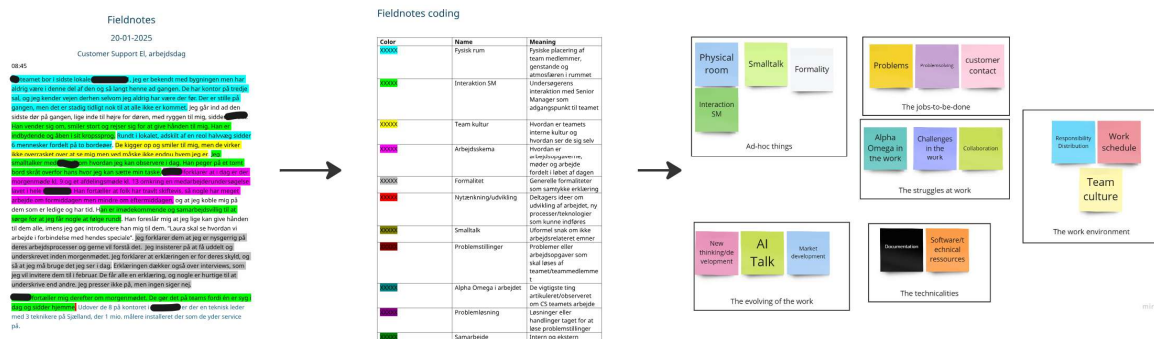


Image 5 – Illustration of the coding and thematic analysis

The codes were clustered into themes by writing them on Post-it notes in the online tool Miro (*About Miro | Meet the Team | Our Mission*, n.d.) and then visually grouping the notes. The analysis yielded four themes related to the users' work practices and environment, which will be presented in Section 5. Thematic coding was used for the Pre-AI witnessing, but for the Conversation of AI, two other analysis methods were used.

4.5.2. Two-cycle coding & Affinity Diagram

The project used a two-cycle coding approach and affinity diagramming to analyse data from Conversations of AI. Affinity diagrams organise qualitative data, facilitating synthesis and visualisation (What Are Affinity Diagrams, 2025). By creating an affinity map, the author identified patterns and converted them into insights, aiming to highlight recurring topics or tension points across interviews. To differentiate between the Conversations of AI components — the P1 semi-structured interview and P2 cognitive walkthrough — the author coded and analysed them separately. Both analyses followed this general approach:

Step 1: Primary cycle coding

Step 2: Secondary cycle coding

Step 3: Name categories

Step 4: Analyse and interpret categories

The specific analysis procedures for the interviews and the cognitive walkthroughs are depicted in Appendices 3 and 4.

Appendix 3 illustrates the data analysis process for P1, utilising transcripts from semi-structured interviews. Step 1 comprised a primary cycle coding of the transcripts line by line, resulting in a list of codes. The focus was on describing what was being said (Gibbs, 2007, p. 52). A codebook was created after the primary cycles to provide an overview of the codes, their descriptions, and their frequencies of occurrence (Appendix

5). Step 2 involved a second coding cycle, where the codes were plotted in Miro and visually clustered into categories. This allowed the author to draw on theories to create clusters (Gibbs, 2007, p. 42). Step 3 involved reevaluating and renaming the categories according to themes and theoretical constructs. Step 4 focused on analysing and interpreting the meanings and tensions of the categories by revisiting the codes and transcripts.

The same procedure was applied to P2 data analysis as shown in Appendix 4, also with a codebook from the primary coding cycle (Appendix 7). The only change for P2 was in steps 3 and 4. In step 3, codes were categorised with P1 categories to relate findings of P2 with P1, with three new categories added for new themes. In step 4, categories were analysed with P1 findings to connect outcomes and identify relationships between imaginaries and experienced agency. Thus, the findings of P1 analysis were used to analyse data from P2. A table summarises the categories from both affinity diagrams of P1 (Appendix 6) and P2 (Appendix 8) with descriptions and codes.

The outcome from the Conversations of AI data analysis enabled the author to answer the research question in sections 6 and 7 through recurring topics and tensions relevant to the theoretical concepts. The analysis will include quotes from transcripts used to illustrate key insights. These quotes are translated into English, since the transcripts included in the appendices are in Danish. For each quote, a page number is given; this number refers to the page on which the original Danish quote occurs in the second file submitted, called "Appendices". All parts of the methodology were chosen to investigate the case most effectively, while also considering the ethical implications carefully.

4.6. Ethical considerations

Following the account of the methodology, this section highlights the ethical considerations made during data collection and analysis. The three overarching considerations were made: *privacy and anonymity*, *bias* and *triangulation*.

Privacy and anonymity considerations ensured the protection of participants' personal information in the project. Participants are not named; they are referenced generally or by an alias. Through informed consent, the author made participants aware of data handling practices. Email addresses and names are stored securely and not disclosed or included in the thesis. All personal information is removed from transcripts and not utilised in the thesis. The focus was on relaying Kamstrup or AI-related information but uphold privacy and anonymity commitments. These considerations led to a critical consideration of bias issues of both participants and the researcher in the thesis.

Bias is a crucial part of reflecting on one's research and role as a researcher. As with everything humans experience, we pass on our own understanding when communicating experiences and stories. The author acknowledges that her pre-understandings and worldviews colour the results and insights. According to Tracy (2020), one of the criteria for quality in qualitative research is sincerity, which involves the self-reflexivity of the researcher's subjective values and biases. This is achieved by being honest and transparent about one's identity, research approach and activities. Therefore, the author acknowledges that her interpretation of the insights was biased by her background in Information Studies and her motives for the project. The author may have overlooked insights or failed to follow up on participants' experiences that fell outside the scope of the research. In addition to her educational background, the author may be biased in her involvement with Kamstrup.

The author's involvement in Kamstrup as an intern in the preceding autumn can have blurred her critical thinking of processes and practices, as she has grown accustomed to them. However, this involvement granted the author knowledge and access to follow a project closely. The involvement also threatened the anonymity of the participants, as the author's past colleagues were aware of her involvement with Kamstrup. They may be able to identify involved teams and individuals. The same applied to anyone involved in the CAI project; they may potentially be able to identify participants based on quotes or

knowledge of the author's activities with the teams. The thesis applied ethical and privacy measures to prohibit this risk as much as possible, but the risks remained to some degree. While the author's bias can affect the findings in a specific direction, bias in the participants' responses may also impact the findings.

Response bias refers to the tendency of participants to answer interview questions in a manner they believe the interviewer wants them to answer (Villar, 2008). The participants thus feel compelled to answer in a certain way as they feel the need to perform well. This phenomenon is also referred to as demand characteristics (McCambridge et al., 2012) or social desirability bias (Villar, 2008). The impact of social desirability happens unconsciously, and so the participants may not be aware of the bias. Dell et al. (2012) highlight demand characteristics as a response bias prevalent in human-computer interaction (HCI). Participants may adjust their answers to align with their idea of the researcher's expectations or societal and demographic influences. The findings of this study may be affected by demand characteristics and response bias, as the participants may be affected by the very situation of being interviewed or by the researcher herself. For example, a participant sought the researcher's confirmation of his understanding of AI. The researcher neither denied nor confirmed this but emphasised that only the participant's understanding mattered. This suggested a bias, as the participant likely sees the researcher as an expert on AI and wants to answer correctly. In these situations, the researcher aimed to emphasise the user perspective, clarifying she was not an AI expert but was interested in their opinions and thoughts. The author highlighted in the interviews and cognitive walkthroughs that she was only interested in their honest opinions, experiences and how they solved the tasks with the CAI. While these declarations were made to mitigate response bias, it was unclear to the author whether all levels of response bias had been eliminated. Additionally, the cognitive walkthrough occurs in an artificial setting rather than as part of the participants' natural workday. Therefore, the participant's task management may be different from their standard

management in a natural setting. However, conducting a cognitive walkthrough always introduces an element of artificiality, as participants are asked to solve tasks while being recorded. Bias can, in this sense, encompass both the author's own bias and the bias of participants in their responses. To ensure that bias does not significantly affect the findings and that the findings have a valid quality, the author emphasised triangulation.

The author focused on triangulation to achieve quality in her research. By striving for quality through the eight big tents of quality by Tracy (2020), the author employed triangulation by collecting different data points to achieve credibility in the findings. In addition, the author employed thick description, through tacit knowledge (cf. 4.2.1) and concrete details, along with multivocality through interviews with members of different teams, to strengthen the credibility of the findings (Tracy, 2021). The focus on quality criteria was not limited to credibility, but the research project was designed to strive for the other tents as well. The methodology was crafted with these ethical considerations in mind but is not without limitations in terms of skills and resources.

4.7. Limitations

The project aimed to create high-quality research; however, practical limitations in resources and skills have impacted the project's structure and outcome. Some of the most impactful limitations are as follows:

- The researcher's skills and knowledge
- Time limitations
- Delays in the organisation

The author had never completed a project of this scale, resulting in a steep learning curve in planning, time management, and readjustment. She relied on her education and skills, guided by her counsellor's advice. The planning and execution had imperfections, making it a valuable learning experience. This was her first empirical project using the selected theoretical and methodological framework. While articles offer guidance,

applying concepts to practice necessitates trial and error. For instance, the author improved her questions and structure from the first to the last Conversations of AI session. Despite the thesis being a learning experience, it impacts the planning and execution and thereby the findings. Developing research skills was crucial for project structure and facilitation, as were time constraints and deadlines.

Regarding time limitations, the project had a 4—to 5-month time frame. This meant it could not be postponed or delayed to address practical limitations, such as a larger participant sample size. The project was thus structured in a way that made it feasible within the timeframe, even though the author could have spent more time witnessing or conducting interview sessions. The time plan was also challenged by delays or changes in Kamstrup's implementation plan for the CAI.

Collaborating with an external organisation provides many benefits, such as access to participants, computers, and real-life cases. However, it also creates dependencies on the organisation's participants and cases. A significant issue affecting this project was the delay in implementing the CAI product, initially planned for the first two months of 2025. Management decisions postponed this, delaying the project's empirical investigations. To adapt, the author observed more teams and invited first-time users for interviews, resulting in a gap in the CAI experience among participants in Conversations of AI. Some were experienced, while others were first-time users. This gap was both beneficial and complicating for the project's results. It introduced diversity in participants' CAI experience, allowing comparisons between the behaviours and perceptions of experienced and new users. However, it may complicate findings with variability in responses. Experienced users may give nuanced insights from prior CAI usage, while first-time users shared initial impressions. Thus, this gap enhanced participant diversity but created inconsistent responses. The same reasoning applied to participants' roles. As discussed in Section 3.1, participants were from customer support and product management teams.

Though closely related, the two teams' purposes and task assignments differed, leading to varying expectations of CAI assistance depending on their roles.

These practical limitations challenged the researcher to reevaluate her position and the project's path. However, keeping the quality criteria in mind, the project's results were deemed valuable and significant in their contributions. The limitations were disclosed to provide transparency regarding the chosen methodology and the reasons for the selection of practices and approaches.

4.8. Methodology summary

The thesis employed an ethnographic and participatory methodology to answer the research question by investigating what is said, the articulated imaginaries, and what is done, the users' reflections and experienced agency in HAIC. The data were collected through participant witnessing, semi-structured interviews and cognitive walkthroughs with a think-aloud approach. The data were analysed in separate tracks, depending on the data collection method, with a focus on recurring topics, themes, and tensions. The recruitment, data collection, and analysis were all conducted with consideration for privacy and anonymity, response bias, and triangulation to ensure credibility and quality. While the project was prone to practical limitations, its findings were still deemed valuable and significant due to the transparency and efforts to address them. Having explained the methodology behind the project, the thesis will proceed to provide the first part of the findings, the themes from the Pre-AI witnessing.

5. The Work before AI

As part of the research activity, Pre-AI witnessing, the author witnessed the users and their teams in their typical workday. Before assessing the impact of CAI implementation, the author sought to understand the work context through an ethnographic examination of the everyday context. The goal was to understand who the

users were, how they worked, and the daily challenges they faced. From the thematic coding of the Pre-AI witnessing fieldnotes, the author has gained an understanding of the work practice, comprised of four themes:

Theme	Description
Human-anchored knowledge and collaboration	The required knowledge and collaboration in the job are anchored in humans.
Broad and complex technical knowledge	The users' technical knowledge covers a broad spectrum and can be quite technical.
Scattered technical documentation	The documentation used to assist with technical questions is distributed widely.
Varying use levels of AI	The users' use of AI in the work and perception of AI in the work

Table 3, Overview of themes from pre-AI witnessing

The results focused primarily on the commonalities witnessed across the three customer support teams. To minimise the identification risk and protect their anonymity, team members will not be mentioned by name, alias, or the team they belong to. Pre-AI witnessing participants may differ from those interviewed in Conversations of AI. The rest of the chapter will elaborate on how each theme in Table 3 was seen in the teams.

A key aspect of the teams' work is that their collaboration and technical knowledge rely on humans. They gain product and technical insights by consulting the appropriate individuals. As one employee noted, hardware-related questions are directed to the product service department, software inquiries are addressed to developers, and feature requests are submitted to product management, highlighting the importance of cross-departmental collaboration. During visits, the author also observed team members regularly seeking assistance from each other. The teams' work is defined by human-centred knowledge, evident in their teamwork and interactions with other departments. This collaboration emphasises a broad and complex understanding of Kamstrup's meters.

The teams address complex customer questions needing extensive product knowledge. A team member compared their broad but shallow knowledge to a colleague's expertise in specific areas. They must be familiar with various product segments, including spare parts and combined products. Due to Kamstrup's custom products, an employee noted challenges in supporting all product types. Their broad technical knowledge often requires teams to look up product details. For example, a member said, "I don't have this by memory; I will have to look it up," when speaking to a customer, before consulting online manuals for solutions. Thus, available technical documentation is vital for accurately resolving customer issues.

The teams' work is hampered by scattered technical documentation, leading to excessive time spent searching manuals. The documentation is located in four primary locations: Kamstrup's platform, commercial resources, the customer support knowledge base, and individual files, such as OneNote. Much of the documentation is too scattered and outdated for quick reference. For example, a colleague from another department asks how to resolve a software issue for a specific product but hesitates to trust the documentation, remembering past errors that caused halted data transfers. The team member reassures him he has the right solution, noting, "even the employees are too frightened to rely on the documentation." This incident highlights the challenges posed by disorganised documentation and the need for collaboration within teams. Document storage presents a significant challenge and can be time-consuming when problems are complex. Alongside documentation, varying levels of AI use are observed among the teams.

After talking to three team members from different teams, the author found varying experience levels with AI. Two out of three indicated that neither they nor their teams used AI in their work. An employee was asked, "Do you use AI?" The person responded, "Well, yeah, we are trying to use it more in Kamstrup." However, when the author explicitly asked, "Do you yourself use AI in your work?", the person replied, "Oh no, I

have never used it. I don't think anyone here [in the team] uses it. " This suggests that the general tendency in Kamstrup is to adopt more GenAI, but this has not yet been realised in specific teams. Conversely, one team member stated that he uses AI in his spare time, particularly ChatGPT, but not in work-related contexts. When discussing the potential of AI, several team members expressed a positive attitude towards the idea of CAI. A team member noted that he could see the potential benefits of implementing AI, such as reduced response times for technical questions, as he could ask the AI rather than colleagues in other departments. The use levels of AI vary in the different teams, but a positive approach is common.

Users' work practices feature close collaboration and broad technical knowledge, challenged by extensive documentation. Required technical knowledge remains vast due to diverse product segments and customisation options. The overall approach to AI is positive, but actual usage varies. This thesis will proceed to explore further how participants understand AI, specifically their constructed imaginaries of AI.

6. Users' imaginaries of AI

Having gained an understanding of the users' daily work practices based on the Pre-AI witnessing, this chapter will focus on the findings from the Conversations of AI research activity. Particularly, the insights from the affinity diagram of P1, the semi-structured interviews. Nine categories were identified from the affinity diagram analysis to help understand the participants' mental models of AI (Appendix 6). A simplified figure below provides an easy overview of the categories.

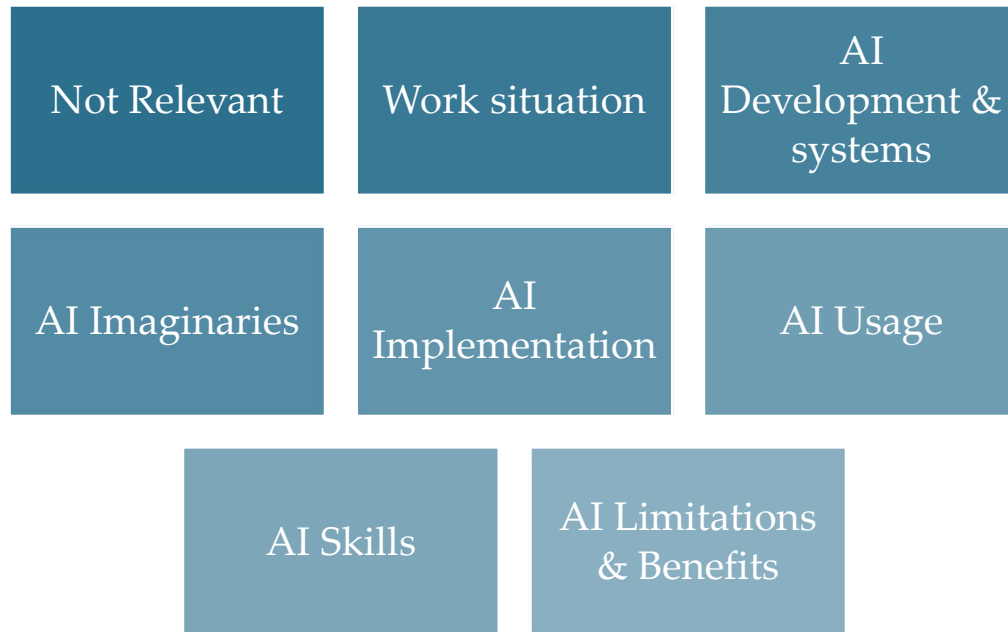


Figure 1, Overview of categories from the affinity diagram of P1

The categories will be used to answer the first part of the research question:

What understandings do users construct about how AI assistants work, and how do these understandings affect users' perceived agency in their interactions and behaviours with an AI assistant?

This chapter focuses on users' understanding of AI assistants, applying categories from the affinity diagram to identify imaginaries. The theory of algorithmic imaginaries helped analyse the understandings that users construct of AI. These understandings will be termed *mental models*, *AI imaginaries* or *imaginaries*, emphasising user perception of AI assistants rather than algorithmic systems, as initially addressed by Bucher (2017). The chapter will begin by outlining the participants' backgrounds and general approaches to AI development. Thereafter, the chapter identifies seven user imaginaries of AI assistants, primarily from the “AI Imaginaries” category. Each imaginary will be analysed using the remaining categories and theoretical foundation. The chapter concludes with a summary of the imaginaries. The findings will include quotes from the transcripts, referenced by page number in the original transcript, in the Appendices.

6.1. The users' background and AI attitude

This section outlines the participants' backgrounds, overall approach to AI assistants, and experience with AI. This will provide a glimpse into the participants' position and perception. The goal is to establish a foundation for understanding the participants' understanding of AI and the sample of participants.

The "Work Situation" category identified users' job titles and experience at Kamstrup, while the "AI Experience & Learning" category revealed their level of AI use. Table 4 provides an overview of the participants' experiences with AI and Kamstrup. The column "Transcript" indicates which appendix contains the given transcript. Aliases are used to ensure the participants are anonymous.

Alias	Role	Work familiarity	AI use level	Transcript
Alex	Solution Manager	1 year	High	Appendix 9
Bailey	Solution Manager	1 year	High	Appendix 10
Charlie	Support engineer	15 years	Low-medium	Appendix 11
Drew	Support engineer	4 years	Low-medium	Appendix 12
Eli	Support engineer	1,5 years	High	Appendix 13

Table 4, overview of the participants' experiences and positions.

Table 4 illustrate how the participants' work experience ranges from 1 to 15 years, with most having spent their careers at Kamstrup. The participants fall into two roles: Solution Manager and Support Engineer. Solution Managers secure solution delivery and

identify customer needs, while Support Engineers address challenges and questions regarding hardware products. Charlie notes their work focuses on service, support, and customer contact. Their educational backgrounds also vary, but they are all technically educated. Some of the degrees include a Bachelor of Engineering in Health Technology or an Electronics Mechanic degree. Despite varied backgrounds and work roles, the five participants share a technically educated foundation and a generally positive attitude toward AI in the workplace.

Table 4 shows that Alex, Bailey, and Eli feel experienced in using AI in work and leisure, while Charlie and Drew have limited exposure. The participants express an awareness and positivity about AI by sharing insights into the technical, developmental, and political features of AI models. Charlie showed an overall awareness and enthusiasm for AI innovation by metaphorically comparing AI development to making pancakes: “The first one is always bad, it is like with pancakes. [...] The first pc that came was also not tip top. And it is the same with AI.” (p. 120) This suggests a recognition of technological development and a belief that AI assistants can improve over time, underscoring an interest in the evolution of AI. Several participants noted that data protection and state regulations influenced their choice of AI assistants. Alex noted, “It really makes a difference in quality and the output you get. [...] Let’s say, if it were a perfect world, where data wasn’t used at all, then it would be ChatGPT.” (p. 33). The quote highlights Alex’s focus on quality and metadata in his choice of AI for work. Additionally, Eli and Alex expressed discomfort with the stringent Chinese regulations on the new DeepSeek AI assistant, illustrating their awareness of the political implications of AI. Not all participants felt they had enough experience to make informed choices; Charlie and Drew mentioned feeling inexperienced in selecting their preferred AI. This insight aligns with the finding of varying use levels of AI among the teams (cf. 5). Overall, the participants demonstrated awareness of the technological, developmental, and political aspects of AI assistants.

The participants hold diverse positions and have varying work experiences, with differing levels of familiarity with AI. Each has a technical educational background. They shared different views on AI's technological, political, and developmental aspects but all have some knowledge of AI assistants. This chapter establishes a foundation for understanding users' activities and general attitudes towards AI. This allows the thesis to explore the users' constructed imaginaries based on the interviews.

6.2. AI Imaginaries

This section identifies users' AI imaginaries, focusing on how users perceive AI assistants on a daily basis. The imaginaries reflect mental models expressed by participants about AI or chatbots. Six AI imaginaries were identified in the “AI Imaginaries” category, with one more found in other categories through participants' stories and sayings. The seven AI imaginaries are illustrated in Figure 2. Participants can construct multiple imaginaries for AI assistants, reflecting various perspectives and nuances.



Figure 2, seven constructed imaginaries of the participants

The imaginaries will be elaborated on and supported by quotations and insights from the remaining five categories of the affinity diagram from Figure 2. The remainder of this chapter will delve into each imaginary and elaborate on the underlying participants' experiences and thoughts on AI and how literature support the given imaginary.

6.2.1. Learning Entity

“It learns everything that it can read” [Drew] (p. 158)

In the first imaginary, AI is understood as a system continuously learning and training on the given data. Drew’s comment encapsulates the essence of this understanding: AI can learn everything it reads. In addition, Alex also explained about the CAI, “You give it a lot of documentation, and then it tries to learn about that. When it has learned about that, then you ask about that documentation.” (p. 48) They both understand the CAI as an entity capable of learning the documentation, enabling them to ask it questions about it. The Learning Entity focuses on AI assistants’ capability to learn from data sets or documentation but also entails an understanding that learning means correcting mistakes.

Some participants view an AI assistant as a Learning Entity that learns from user corrections. In the AI Skills category, Bailey mentioned he frequently writes to AI assistants because he receives incorrect answers. “Are you sure that that is right?” (p. 90) is what he says he writes to the AI, indicating he thinks AI can learn from mistakes. Eli highlighted that the effectiveness of AI assistants depends on their preparation (from the AI Limitations & Benefits and AI Experiences & Learning categories). He preps the AI by demanding specific answers. For example, he said that he asks AI, “What do the experts say in the different investor sectors? What do they say, for example, about this stock, so I myself can assess it?” (p. 203) Instead of simply asking which stocks to invest in, Eli teaches the AI to align with his preferences. The Learning Entity concept reflects distinct behaviours and strategies in user interactions with AI. Relating to Bucher’s popularity games (2017, p. 37), Eli aims for maximum effectiveness and personalisation of the AI assistant. In the imaginary of the Learning Entity, users use strategies to enhance the AI experience, similar to optimising the Facebook algorithm (Bucher, 2017). Bailey and Eli foster a synergistic relationship by training AI algorithms. Users correcting mistakes and offering feedback enable a more collaborative dynamic, as this allows the AI to meet user

needs better (Sundar, 2020). For participants who see AI assistants as Learning entities, the model suggests that AI continuously learns and enhances its performance. This imaginary relates to strategies for optimising and training AI for personalised experiences. The Learning Entity connects closely to the next imaginary, where users view AI as a system that indexes and processes data for improved responses.

6.2.2. Data-driven System

“They have, of course, as I understand it, a lot of knowledge indexed because it was trained on that”

[Alex] (p. 41)

Some participants understand AI as a data-driven system that indexes and processes enormous amounts of data to generate responses. Both Bailey, Alex, and Eli expressed a view that an AI assistant is trained on extensive data, which serves as the foundation for its responses. They see the AI's answers as grounded in historical data from the same region or related data relevant to the area of interest. Bailey emphasised understanding AI as a system predicting user intentions to provide accurate responses from historical data. “It’s a chatbot that, through calculation, tries to predict what answer you are searching for or what information you are looking for, ” (p. 79) Bailey explained. This view relates to the data-driven system, but Bailey adds a dimension of prediction to his imaginary. Understandings of the data-driven system can vary among participants and is closely connected to certain behaviours.

The data-driven system is evident in some participants' skills when interacting with AI assistants. “In cases of CAI, I always ask it to give quotations for documentation, to ensure that what comes out is correct,” (p. 42) stated Alex from the AI Skills category. He stresses the importance of obtaining quotations from the CAI to confirm the accuracy of generated responses. Like Alex, Bailey said he used this skill to avoid incorrect answers. This citation skill demonstrates that both are aware of the system's capability to generate responses from large datasets and understand that AI assistants index data. They prompt

AI to request specific data points or quotations in documentation. The concept of a data-driven system aligns with Ngo's view of algorithms as data structuring, meaning they are grounded in and developed from data (2022). This understanding suggests a tangible-oriented view of algorithms and AI. Data-driven System depicts AI assistants in an input-process-output understanding.

The Data-driven system imaginary highlights a tangible-oriented understanding of AI as a system that indexes and processes data. The imaginary is closely linked to behaviours of specificity prompting, such as asking for exact quotes from the data. The imaginary highlights a technical view of AI; however, some participants understand AI from a more sensitive or ethical perspective, conceptualised in the Emotionless Agent imaginary.

6.2.3. Emotionless Agent

"It doesn't have emotions or anything" [Drew] (p. 163)

Some interviews articulated an understanding of AI as lacking emotions or moral considerations. The Emotionless Agent highlights AI's inability to feel, as Drew stated, or understand morals, leaving the moral compass to the users. Eli explained, "Based on how we prep it, then it is not going to answer one way or another. And then it is our responsibility, how we use it" (p. 207), where he highlights the users' responsibility to use AI morally, as the AI itself does not consider things such as immoral topics. Alex also mentioned how the AI may be trained on incorrect things without knowing what is correct or incorrect. As with the Data-driven system and Learning Entity imaginaries, this one is also closely linked to specific behaviours or approaches to interacting with AI assistants.

The Emotionless Agent imaginary suggests a cautious interaction approach with AI assistants. The participants are careful in their dealings with AI. Alex noted, "My observed opinion is that you have to take everything about AI with a grain of salt... so a certain cautiousness." (p. 34) His cautious stance reflects concerns about public AI assistants using

chat data and metadata for external sales (cf. Section 6.1). The Emotionless Agent model suggests that these users perceive AI as lacking nuanced judgment, potentially leading to distrust in AI (Molina & Sundar, 2024). The Emotionless Agent enhances the view of AI lacking a moral compass and requires users to be cautious about AI's outputs.

The perception of AI assistants as emotionless agents stems from stories of malicious AI use. Drew recounted tales of "how AI has been racist or those scary stories. Right? Like those who have also helped people commit suicide or how to do it in the best way." (p. 163) Such stories reinforce the belief that AI assistants lack awareness of moral issues. Eli also heard of people asking ChatGPT about committing murder undetected; when declined due to regulations, users rephrased their questions as if writing a book about evading homicide and then received responses. This illustrates how workarounds can circumvent ethical regulations because AI is unable to detect context or emotional distress. A user's view of AI is shaped by personal experiences and societal narratives, including concerns about misinformation and unethical use, contributing to a negative perception (cf. 2.2, p. 15). Thus, negative machine heuristics seem to underlie the Emotionless Agent image, as negative perceptions arise from participants' experiences and societal anxieties (Sundar, 2024). Although AI can positively impact user skills, critical concerns may lead to cautious AI use, limiting the benefits (Giordano et al., 2024). User imaginaries are influenced by fears of negative societal impacts from "scary stories" and unethical AI practices.

The Emotionless Agent AI imaginary entails understanding AI as incapable of having feelings or a moral compass. The imaginary stems from negative experiences, unethical use of AI, and concerns about societal impact, which can lead to a cautious approach to AI assistants. Despite the emotionless perception of AI, some participants still see great potential in an AI assistant as a helpful personal assistant.

6.2.4. Personal Assistant

“As a sparring partner and for help and for information search” [Bailey] (p. 76)

All participants viewed AI assistants as helpers in answering questions or finding information. As Bailey noted, AI is there to help and spare with users. The idea of AI as a personal assistant is widely held, as evidenced by how participants utilise it as such.

The concept of a personal assistant emerges in the participants mentioned use cases of AI. Notable use cases in AI include Technical Applications, Text Formulation, and Information Search (from the “AI Usage” category). Technical Applications involve AI assisting with code scripts and processes, such as optimising CSV file processing and improving API scripts. Bailey and Alex have applied AI for these purposes in their work and educational projects. In Text Formulation, three participants reported using AI to rephrase and edit text both in work and leisure contexts. For example, Drew mentioned he used AI to make customer emails more professional. Lastly, participants utilised AI for information search, enabling the quick retrieval of answers. Eli said he used an AI assistant to extensively research topics, saving time. All use cases portray AI as a personal assistant that enhances daily productivity and benefits the users.

In the category “AI Limitations & Benefits”, all participants saw AI assistants as optimisers for their work. “It goes a bit faster than if I myself should sit manually and put it together,” (p. 118) Charlie said when he talked about AI's effectiveness. To Charlie, an AI assistant can optimise his work performance by saving time and expenses. Participants noted potential benefits of the CAI: optimising work, reducing response time, and improving customer satisfaction. The current work practice is characterised by scattered technical documentation (cf. 5), which can be time-consuming for employees. The personal assistant's benefit is closely tied to a desire to reduce the time spent searching for documentation. Giordano et al. (2024) also highlighted the benefits of using AI for brainstorming and text formulation in various occupations, aiming to increase

productivity and save time for more creative or demanding tasks. A successful HAIC is characterised by the AI and user collaborating on different tasks to reach a common goal (Fragiadakis et al., 2024). The Personal Assistant highlight AI assistants' role in making things better for the users to reach new performance levels. In this mental model, AI assistants are highlighted for their potential to improve time and work efficiency.

The Personal Assistant entails AI assistants helping users with their needs. This is evident in the participants' AI usage, including Technical Applications, Text Formulation, and Information Search. This view portrays AI assistants as beneficial for optimising work performance and reducing time on tasks. The idea of AI's capability to enhance practices also underlines the Super-computer imaginary, where AI has superhero-like abilities.

6.2.5. Super-computer

"I am thinking that you have prepped a supercomputer with a lot of information" [Eli] (p. 205)

Some participants envision AI as a supercomputer or robot, limited only by users' imagination. This model portrays AI as highly advanced and complex. As Eli stated, an AI assistant has a processing power bigger than ordinary computers, emphasising that its algorithmic processing surpasses human information retrieval. This notion contributes to the "super" in super-computer, suggesting that AI's processing operates on a higher level, going beyond most users' abilities.

For one participant, the view of AI assistants as super-computers entails the idea that they demand specific technical skills to use them effectively. Alex noted that for users to benefit from AI, they need specific skills. He stated, "If there sits a like...an elder not so technological gentleman or lady, who hasn't really used it much before, then they might take what it answers as the definitive truth." (p. 51) This highlights an idea that not everyone can easily utilise an AI assistant; it requires critical thinking and a understanding of how AI works. If Alex viewed AI as an "average computer," he might not add special notice to the skills needed to use it, underlining Alex's image of AI as highly advanced and

complex. Despite this dimension, Alex and the other participants see AI as beneficial in optimising their practices and performances.

The supercomputer model presents AI as beneficial and capable of improving performance. In sections 6.1 and 5, insights suggest that team members and participants generally have a positive attitude toward AI, believing it enhances work efficiency. Drew's statement resonates with these insights: "My thought is that it is the way we are going. We must all get better at using it" (p. 156), emphasising his commitment to AI. He sees AI as essential for Kamstrup's future and looks forward to its improvements. All participants regard AI assistants as beneficial for enhancing processes and managing knowledge. Their optimism suggests that AI could surpass human abilities, improving performance limited only by imagination. The AI as a supercomputer thus relates to a positive machine heuristic, where users believe AI is more capable and objective than humans (Molina & Sundar, 2024). Like the Emotionless Agent and negative machine heuristics, users' attitudes are influenced by their experiences and views of AI. By expressing high expectations of AI's capabilities, participants envision AI as more competent than humans in specific tasks.

The concept of a supercomputer imaginary encompasses the idea of an AI assistant that exceeds human capabilities and is highly beneficial for work performance. However, the imaginary can imply that only technologically skilled users can unlock AI's potential. The supercomputer mental model is closely tied to positive machine heuristics towards AI. Moving on from a technically focused imaginary, the following model centres on the communicative aspect of AI assistants.

6.2.6. Communicative partner

"Suddenly, you forget you are sitting and writing with a computer, right?" [Drew] (p. 159)

Drew's quote shows that AI assistants are conceptualised as communicative partners, enabling interaction with participants and serving as sparring partners. As can be seen in the quote from Drew, AI assistants mimic human message communication when they collaborate. Bailey connects the Communicative Partner concept with "To save or eliminate a need for human interaction. So, to make processes easier. " (p. 83) This highlights AI's role in optimising performance in work contexts. The participants' teams often rely on colleagues for answers (cf. 5), but, as Bailey noted, AI can help users independently find solutions, potentially changing their internal collaboration. The Communicative Partner supports users by fostering independence and serving as a collaborative partner.

The Communicative Partner's purpose is also clearly visible in the participants' uses of AI (from the "AI Usage" category). For this imaginary, use cases include Study Buddy, Idea Generation, and Sparring Partner, highlighting a communicative and conversational use context. The Study Buddy use case involves utilising AI assistants to aid in studying or preparing for an exam, and is mentioned by Alex and Bailey, who utilised AI during their education. Alex used AI assistants to explain complex concepts differently, which helped him better understand the curriculum. Communicative Partner is visible in how participants communicated with AI as a study buddy to understand and learn new things. In addition, Eli, Bailey, and Alex used AI assistants for idea generation, whether planning an event, writing a job application, or creating a training plan. Accordingly, they found AI to be a good partner for ideation and brainstorming. By engaging in a collaborative discussion with an AI assistant, participants experience easier idea generation and gain new perspectives on their situation. Lastly, participants mentioned using AI as a sparring partner to discuss topics in both professional and leisure contexts. For example, Drew mentioned that he had seen AI assistants being used to simulate a different personality. "But you can ask it to answer you as if whoever you want, to spar with you in so and so step into the role", (p. 158) was how Drew explained using AI for role playing, such as

Dungeons & Dragons. The use cases highlight the various experiences participants have of engaging with AI conversationally and collaboratively, constructing the model of AI as a communicative partner.

This imaginary relates closely to the Personal Assistant model but emphasises more conversational collaboration. While the Personal Assistant focuses on providing help, the Communicative Partner centres around user dialogues with AI, for various purposes or contexts. The Communicative Partner is closely related to what Fragiadakis et al. (2024) refer to as a *symbiotic mode* of HAIC. This mode of HAIC involves a balanced relationship with a two-way interaction. Clear communication is vital in symbiotic mode for users to comprehend AI responses. Ideally, this collaboration complements human intuition with AI capability (Fragiadakis et al., 2024), showcasing how AI reshapes communication and reduces the need for human interaction. Similarly, the Communicative Partner focuses on an interactional relation between AI and users to help them constructively with their endeavours and problems.

The Communicative Partner illustrates an imaginary vision of AI assistants as collaborative sparring partners capable of engaging in dialogue with users. The imaginary is anchored in the participants' use cases of AI, such as Sparring Partner, Idea Generation and Study Buddy. The imaginary closely relates to the Personal Assistant but differs in its interactional focus and symbiotic mode of HAIC. Having examined both technical, communicative and ethical understandings, the following model introduces another form of imaginary that focuses on AI's ethical and sensitive aspects.

6.2.7. Fallible Agent

“The first, I think, is a lot in how I use it myself. Sparring partner. But I also think instantly of error” [Alex] (p. 34)

AI assistants are viewed as helpful but fallible systems that can make mistakes. This understanding highlights the imperfect nature of AI. The Fallible Agent concept is

prevalent in the participants' critical perspectives from the "AI Experience & Learning" category. For instance, Drew developed his critical mindset after watching a TV program on AI, learning what to scrutinise in AI interactions. He gained this understanding from TV, which shaped his critical approach. Similarly, Bailey noted, "You have a critical approach to what you get to know from there [the AI], and maybe also a bit of technical understanding of why it sometimes makes those mistakes." (p. 80) Both Bailey and Drew perceive AI assistants as fallible, believing they must critically question the AI's responses. Their perceptions are founded on experiences of AI inaccuracies or errors. One reason users may choose not to adopt AI assistants is poor output quality, including incorrect answers (Janssen et al., 2017). These mistakes can erode trust in AI; as such, if Drew or Bailey encountered errors, their interest in using AI may decline. However, these errors can also serve as opportunities to correct users' perceptions of AI assistants (Böckle et al., 2021). In these instances, users can offer feedback, aiding AI development and improving its learning experiences. Incorrect responses from AI have influenced several participants to develop validation skills (noted in the "AI Skills" category), suggesting they expect or have experienced false answers from AI. This skill may stem from a critical approach but can be valuable for the user to determine if the AI meets their expectations (Giordano et al., 20204). Ultimately, users' experiences can improve by adjusting their mental models to account for AI's fallibility and cultivating their skills in evaluating AI outputs.

Understanding AI assistants as error-prone and imperfect is central to the concept of the Fallible Agent. The participants' understandings stem from experiencing false answers and approaching AI's answers critically. The Fallible Agent show how errors impact user adoption but can provide opportunities for readjusting mental models or developing validation skills. The Fallible Agent is the last of the seven imaginaries, illustrating how users can construct varying mental models of AI and how they should interact with it.

6.2.8. Summary of imaginaries

Based on the affinity diagram analysis, the participants construct seven imaginaries of AI assistants' functions. The imaginaries can have varied focal points for AI systems. Some focus on the advanced technical capabilities of AI, such as Super-computer, Data-driven Systems and Learning Entity. They can also focus on the interactional purpose of the AI, such as the Personal Assistant and Communicative Partner. Lastly, the Emotionless Agent and Fallible Agent are imaginaries centred on AI's sensitive and ethical nature. Overall, these imaginaries provide users with a means of understanding AI assistants and how to interact with them effectively.

7. Agency in HAIC

Having addressed the first part of the research question, the thesis will move on to the second part:

*What understandings do users construct about how AI assistants work, **and how do these understandings affect users' perceived agency in their interactions and behaviours with an AI assistant?***

This chapter will focus on users' understanding of AI assistants from chapter 6 as impacting their SoA in interactions with the CAI. The seven AI imaginaries are compared to insights from categories in the affinity diagram for P2 (Appendix 6). Section 7.1 will provide an overview of the seven imaginaries from Chapter 6. Section 7.2 will dive into each imaginary and its impact on the participants' agency and behaviours. The following section will examine three factors that play a role in the relation between imaginaries and agency and influence the HAIC. Lastly, 7.4 will summarise the findings in key takeaways.

7.1. Overview of imaginaries

As per Chapter 6, seven AI imaginaries were identified based on the insights from the affinity diagram of P1. The following table provides an overview of the imaginaries and their belonging descriptions.

<i>AI Imaginary</i>	<i>Description</i>
Learning Entity	AI assistants are understood as systems that continuously learn and train on the given data or information.
Data-driven system	AI assistants are understood as a data-driven system that indexes and processes enormous amounts of data to generate responses.
Emotionless Agent	AI assistants are understood as lacking emotions or moral considerations.
Personal Assistant	AI assistants are understood as helpers and personal assistants to the users.
Super-computer	AI assistants are understood as a supercomputer or robot, where one's fantasy sets the limits.
Communicative Partners	AI assistants are understood as communicative partners capable of interacting and discussing collaboratively.
Fallible Agent	AI assistants are understood as imperfect systems capable of making mistakes.

Table 5, overview of identified AI imaginaries

Table 5 provides an overview of the imaginaries, along with a brief description of each. As mentioned in the introduction, agency and alignment in human and AI agency are crucial for user adoption of AI (Araujo et al., 2020). Users' mental models, or imaginaries, help them identify how to exercise their agency (Kang & Lou, 2022). Agency is thus included in the analysis to understand how agency correlates with users'

imaginaries of AI. This chapter will explore how the participants' imaginaries of AI assistants affect their interactions with them.

7.2. Impact of AI imaginaries on User Agency

This section will analyse how each imaginary influences the participants' SoA in interactions with the CAI. Appendix 6 shows the imaginaries as categories from P2 analysis with a belonging description and codes. Quotes from the participants and points from the literature will support the findings. The translated quotes from the original transcripts will be referenced by page number in the attached file "Appendices". The analysis will begin by looking at how the Learning Entity influences users' behaviours with the CAI.

7.2.1. Learn to trust

The Learning Entity's imaginary influences participants' behaviour and expectations of the CAI, affecting their SoA. Participants see the CAI as learning from interactions, raising their expectations for the system's improvement. Drew noted this expectation, assuming the CAI learns from its mistakes.

That's my expectation, actually—just a little—and it's that it's self-learning and that it should get better and better. [you hope it saves all chats and learns from them?] Yes, but isn't that what AI does? [Drew] (p. 186)

Drew feels a sense of control from the expectation of AI improvement, believing his interactions influence it. When participants believe they have influence over the AI, their feeling of control increases (Shneiderman, 2020), thereby enhancing their SoA. Like Drew's understanding, literature suggested that a key AI characteristic is its ability to learn from user input, allowing users to "train" algorithms and exercise agency over the system (Kang & Lou, 2022). According to this understanding, the CAI should

automatically learn from the user's input. The imaginary thus suggests that the user can impact the CAI's learning development through their prompts and input.

Users' mental models guide specific ways to exert their agency; as such, the Learning Entity entails an exercised agency through mistake correction acts, as Bailey mentioned (cf. 6.2.1) and as Alex did in the walkthrough (p. 68). In human-AI interactions, both parties exhibit agency and intentionality (Borsci et al., 2024), indicating mutual influence. For the participants, mistake correction represents user agency influenced by AI responses. This behaviour entails users trying to control their experience and affect the CAI's learning process. However, AI's opacity obscures the perceived link between correction and learning, leading to user scepticism about its learning capabilities.

Doubts about AI's learning can reduce user agency. When Drew doesn't get proof the CAI learns from conversations, he becomes weary and doubtful. "But that's probably where I question, does it get more and more skilled? I would probably just like to confirm that," (p. 188). A lack of proof in the Learning Entity imaginary decreases Drew's engagement and SoA in the CAI's improvement. Drew constructs a mental model of the CAI based on an algorithmic presence, which refers to potentially unknowable algorithms (Wang, 2023) but lacks proof in his interactions. According to a developer, the CAI does not iteratively learn from all user chats (cf. 3.2). This misalignment happens because the user is unaware of this limitation, and the CAI's opacity provides no transparency. Lack of transparency in AI systems hinders the easy understanding of system processes and fosters uncertainty among users (Liu, 2021). The misalignment leads to participants' AI imaginaries being far from the actual capabilities, making collaboration with AI more challenging. However, users are not expected to understand AI's technicalities. The CAI aims to serve users in customer support and product management, who have varying levels of AI experience (cf. 5). Requiring high AI technical proficiency would exclude users and hinder successful HAIC in the teams. The gap between expected functionality and actuality reduces users' control and influence in the AI assistant's development.

The Learning Entity imaginary affects participants' agency through expectations of improvement and trust in the system. Doubts about learning capability can create uncertainty and weariness in user behaviour. Trust in meeting expectations influences feelings of agency and control in AI learning. Uncertainty also impacts the Data-driven System imaginary regarding participants' behaviour.

7.2.2. What and where is the data?

The data-driven system's imaginary highlights AI's ability to process large amounts of data for responses. The imaginary impacts the participants' SoA through fact-checking and the use of background knowledge.

The participants understand the CAI as a system that collects and processes data, so they assess the CAI's output to exercise their agency over the interaction. Alex stated, "So I have a lot of my own knowledge if I can use it to verify whether things are correct" (p. 53), explaining why and how he assesses the accuracy of the CAI's responses. This example shows how technical knowledge of Kamstrup's product documentation is used to evaluate CAI's outputs. When the participants experience alignment between their background knowledge and the CAI's output, their SoA is strengthened because their action gave the expected output (Pagliari et al., 2022). As seen in 5, the work is characterised by a broad and technical knowledge, meaning the users possess a significant amount of knowledge accumulated through their work. With the CAI answering work-related questions, the user's background knowledge sets expectations for what constitutes correct or sufficient answers. If the users' expectations are met, their imaginary is reinforced that the CAI has the right data, and their SoA is strengthened. This dynamic suggests that user imaginaries and SoA are not static but mutually shape each other. As users engage with the AI, their Data-driven imaginary is evolving, which influences their perceived agency and how they decide to exercise their agency. In addition to background knowledge, fact-checking behaviour is found to be an act of agency from the Data-driven System imaginary

The data-driven imaginary also impacts the participants' behaviour as they employ a fact-checking strategy. Eli demonstrates this when he specifically looks for an info-code, displayed in some products, in a technical description to see if the CAI has provided him with the correct info code (p. 223). In this scenario, Eli exercises his agency by fact-checking documentation to know if he should correct the CAI or rely on its answer. Due to GenAI's issue in making hallucinations, a realistic but nonsensical answer (Waldo & Boussard, 2025), users risk becoming over-reliant on the AI assistant and its potential misinformation and false content. Users can minimise the risk and develop their critical thinking by fact-checking an AI's response (Lee et al., 2025). Eli's fact-checking behaviour can thus stem from his technical data-driven understanding of AI as a system based on training data and being prone to hallucinations. This relates to how users who understand the consequences of using AI, such as hallucinations, feel more in control of their experience with AI (Shneiderman, 2020). Due to the Data-driven System understanding, Eli influences the system through fact-checking behaviour to exercise his agency and gain control.

The data-driven system imaginary affects the users' SoA in their use of background knowledge and fact-checking behaviours. Assessing results and employing fact-checking is used to navigate hallucinations and evaluate the CAI's data processing. The critical approach employed here, through fact-checking, is also evident in users who act based on an Emotionless Agent understanding of AI.

7.2.3. Question the lack of emotions

Expecting the CAI to have no emotions or moral compass, as per the Emotionless Agent imaginary, leads users to employ a critical and cautious approach. The imaginary affects the users' SoA and trust in their interactions with the CAI.

The emotionless understanding of AI assistants can both stem from stories of and affect users to work around safety regulations. During Task 6, Alex was denied a baking

guide due to topic limits but worked around the limit by asking in English or starting a new chat. When asked why he kept prompting, he stated, “Because I’m stubborn and because I know that there is usually always a way around.” (p. 71) He also mentioned that he knows how to manipulate AI assistants by claiming he is writing a story instead of asking directly. This workaround behaviour in stories of misuse constituted Drew and Eli’s imaginary of AI as an Emotionless Agent. The emotionless understanding can thus be constituted from stories of misuse and influence the user to act in a circumventing behaviour. For Alex, the imaginary influenced how he exercised his agency through a workaround to achieve his desired answer. In addition to the workaround, the Emotionless Agent can also impact a critical behaviour in the participants.

All participants demonstrate cautious behaviour when using the CAI, questioning its accuracy. Drew experienced the CAI inaccurately stating that a component could be changed in a compact product and noted, “It probably just tells me that what it [CAI] writes to me, I have to be quite critical of that, because it may say that I can change the module in the meter.” (p. 186) This reinforced Drew’s critical and cautious approach from the Emotionless Agent imaginary and lowered his trust in the CAI’s accuracy. Users’ critical and cautious behaviour is increased when faced with inaccuracies or false answers. It can trigger negative reactions that lead to algorithmic aversion—a preference for human judgment over AI (Sundar, 2020). Users’ trust in AI diminishes because they feel a loss of control and unmet expectations. The Emotionless Agent fosters general aversion and distrust among participants when they encounter inaccuracies, suggesting a lack of nuanced judgment in the CAI. These experiences shape users’ view of the CAI as an emotionless agent, influencing their behaviour to exercise agency in workarounds and cautious approaches. This correlation suggests mutual shaping between users’ imaginaries and SoA when interacting with AI. The user’s perception and perceived agency continuously inform each other as they collaborate with the AI.

The Emotionless Agent imaginary influence users' critical and cautious approach to interactions with the CAI. The imaginary is tied to the users' trust in the system's accuracy. The users' SoA is exercised when they make workarounds past regulations. The imaginary may cause an algorithmic aversion and general cautiousness when the users experience the CAI's lack of judgment that resonates with the imaginary. The exercising of agency as shaped by the users' imaginary, suggesting a mutual shaping between the two. The mutual shaping is also prevalent in how the Personal Assistant affect users' agency.

7.2.4. Personal potential

The Personal Assistant fosters high expectations regarding the CAI's practicality and usefulness. When participants' needs for personal help are met, they experience high satisfaction and a sense of control. As an example, Alex received answers that met his expectations and when asked if he could use the answers for customers, he said, "If they [customer] asked me why it can't be from earth connections..." (p. 60) and then he mimicked a copy-paste action on the keyboard with a smile. Alex's expectations for personal assistance from the CAI are met, resulting in an expression of high satisfaction. Because Alex received a satisfying answer meeting his experience, his SoA is strengthened as his needs are met. This suggests that the CAI's role as a personal assistant is closely tied to users' expectations for its performance.

On the contrary, if expectations are not met and communication is misaligned, the user's satisfaction and SoA diminish. Drew expected specific answers from the CAI to relay to the customer but felt frustrated having to sift through responses to find the relevant information. When seeing an answer, Drew expressed, "Well, I would sit and spend a minute on just and... So, I must filter it and say, what has this to do with it? And is there anything I can use?" (p. 183) To Drew, the CAI's answer needed to be more concise so he could easily understand it while speaking to customers. Drew's expected outcome of his prompt is unaligned with the actual output, which challenges his SoA. This is explained by the fact that when users feel AI enhances their performance and its output is

predictable, they experience a higher SoA and control in the interaction (Pagliari et al., 2022). For Drew, the opposite happened as he felt hindered in doing his job well, and his expectations were unmet by the CAI. The Personal Assistant imaginary influences users to expect a personally aligned interaction that enhances their work performance. When the imaginary is challenged, participants experience dissatisfaction and a weaker SoA. This highlights a mutual shaping between the participants' constructed mental model of a Personal Assistant and how they experience their own SoA. During their interactions, the participants evaluate how well the CAI fulfils their Personal Assistant's imaginary, developing their understanding. The evolving imaginary shapes how the users behave with the CAI, if their expectations are met or if they need to influence the system through their agency. As Janssen et al. (2021) concluded, AI chatbots fail when they cannot meet users' expectations for trust, ease of use and usefulness. As such, when the participants expect CAI to be a Personal Assistant that makes things easier for them and is easy to collaborate with, they can feel discouraged about using it if their imaginary falls short of reality.

Understanding an AI assistant as a personal assistant can foster expectations of practicality and usefulness. Users expect specific communication patterns and high satisfaction with the AI's responses. When the imaginary is unmet by reality, the users feel less agentic and more dissatisfied with the collaboration. High expectations of the AI's capabilities are also prevalent in Super-computer imaginary connection with the users' behaviour.

7.2.5. Super challenged

The supercomputer mental model sets high expectations for precision and efficiency in the AI assistant. The participants experience a strong SoA when the CAI matches their supercomputer mental model.

From 1-10, how precise? I would say 9 out of 10 and the last one out of 10. That's when it makes a mistake once in a while. No, I don't want to... I would say I must say 99 out of 10. I actually think it does insanely well. [Bailey] (p. 106)

When Bailey rated the CAI's answers, he expressed excitement and satisfaction with its precision. Because the CAI's performance aligns with his expectations, his sense of control increases since his understanding of the CAI matches the reality. This example supports the connection between positive machine heuristics and user behaviour (cf. 6.2.5) for the Super-computer imaginary. Bailey sets expectations for the CAI to be more capable than humans, and due to his experience and strengthened SoA, it reinforces his understanding and positive attitude. However, this is not always the case; sometimes, the user's SoA and imaginary are challenged.

A user's SoA weakens when encountering irrelevant or incorrect outputs, misaligning the participant's super-computer imaginary with reality. Similar to the Personal Assistant, when the participants must filter through the CAI's answers, it challenges their SoA because the CAI's outputs are far from the participant's expectations. Both Eli and Drew found the CAI to provide extra information that hindered their task-solving rather than improving it. On the contrary, Alex was satisfied with the extra information as he got what he wanted and more. This highlights the mutual shaping between the imaginary and the participants' SoA. For those instances where the imaginary closely aligns with reality, such as AI providing additional information, the feature serves as an amplifier rather than an obstacle. Extra information weakens some participants' SoA, due to misalignment between the imaginary and reality, which is further hindered by CAI's opacity. The black-box nature of AI limits transparency, complicating their SoA (Pagliari et al., 2022), such as when users are unable to understand AI's responses. The Super-computer imaginary suggests a positive attitude toward AI (Ngo, 2022), implying that AI is a superpower that should perform exceptionally (cf. 6.2.5). When these high-performance expectations are unmet it negatively impacts the satisfaction and SoA.

Findings show a link between Super-computer imagery and users' learning and skills, as articulated by Alex in his imaginary (cf. 6.2.5). Alex and Bailey, who are regular CAI users, did not experience the same level of frustrations as the other participants. This suggests that users' experience with the CAI is crucial for collaboration. In contrast, Drew, Eli, and Charlie, infrequent users, experienced more frustration when their expectations exceeded the CAI's capabilities. Supposedly, Alex and Bailey felt a stronger SoA due to their imaginary of the CAI being more adjusted. They likely have encountered more AI errors in their usage, leading to a greater alignment of their imagination with the AI's performance (Böckle et al., 2021). This difference also demonstrates how past experiences and performance levels influence users' SoA and heuristics toward AI (Wang, 2023; Pagliari et al., 2022). Some Participants had different experiences, which altered their SoA and heuristics, and thereby their imaginaries, compared to others. This difference can be explained by the theme of varying use levels of AI (cf. 5) and the participants' different experience level of AI (cf. 6.1). Additionally, this difference shows how a user's understanding of an AI assistant mutually shapes their SoA and evolves together as the user gains experience. Positive experiences that enhance performance can strengthen agency and align the supercomputer's imaginary with the AI's actual abilities.

Overall, the supercomputer imaginary may create high expectations for AI capabilities, sometimes to an exceptional level. Users' agency strengthens when their mental model aligns with reality after multiple experiences with the CAI. Findings suggest that this alignment is linked to users' experiences with and learning about AI. While the super-computer focuses on the technical expectations of AI, the Communicative Partner highlights the relational dimension in how users exercise their agency.

7.2.6. Communication clarity

The perception that AI is a communicative partner insinuates that AI systems can engage in meaningful conversations and collaborate with users in a manner that makes human interaction less necessary. The Communicative Partner imaginary fosters

expectations for the AI system to understand conversational cues or patterns. Users' SoA is strengthened when they experience the AI communicating in a way that meets their expectations. However, findings suggest that expectations can differ among the participants. Regardless, some expectations are expected among all of the participants, such as being specific, regardless of the conversational pattern.

All participants emphasise specificity in prompts and context for the CAI. "I thought to ask it very specifically, if you can configure the CT-ratio, and then very specific about a Kamstrup meter so that it knows what we are talking about," (p. 57), Alex said when formulating a prompt. He provides contextual information because he expects general answers from the CAI but seeks specific responses about Kamstrup's products. Unlike their usual way of asking a co-worker, where the context is clear (cf. 5), Alex feels the need to clarify for the CAI. His approach reflects his imaginary of the CAI may lack the necessary context, and strengthens his SoA by influencing the outcome of communication. In addition to context specificity, follow-up questions are often an expected part of communication with the CAI.

Several participants use follow-up questions to gain clarity on the CAI's answers. As Charlie explains, "and then ask, 'how do I do it?' in a way, I think it is fine that you start out with such an open question and then you boil it down afterwards." (p. 142) He expects to follow up with questions to achieve the desired responses. He assumes a funnel-like conversation pattern, starting broadly and prompting the CAI until he gets the desired specificity. This pattern provides him a sense of control over the conversation. Charlie influences the CAI and then experiences it, following his conversational pattern, which creates a strong SoA. Guiding the CAI toward its goals enhances the user's sense of control, as their actions lead to the expected outputs. Conversely, when expectations misalign with actual communication patterns, it can challenge the user's SoA and imagination.

If users feel misunderstood by the AI because their communication patterns do not align, it can weaken their SoA and cause frustration. Inaccuracies and changing responses by the AI can create this misalignment. For instance, Alex experienced the CAI changing its answers during their chat. When Alex realised the change in the CAI's answers, he surprisingly exclaimed "wow wow", and added "It is, that it went from saying that the meter can communicate RF to that, which is correct, is that it now communicates with NB-IoT and LTE-M." (p. 63). Alex's Communicative Partner imaginary encouraged him to ask questions and guide the CAI, but he struggled with incorrect responses. Alex exercised his agency by prompting the CAI, resulting in his desired answers, but confusing communication. Communicative Partner is tied to users' communicative behaviour with the CAI, where users exercise their agency through small acts to maintain control (Kapsch, 2022). In this case, Alex's prompting was an act to get the CAI to answer correctly and gain control of the conversation. This relation suggests a link between the Communicative Partner, SoA and communication alignment. The link highlights a mutual shaping correlation where a user's communication approach shapes their agency, and in turn, exercising agency influences their mental model of the AI's communication.

In summary, the Communicative Partner is tied to the user's SoA regarding expectations and conversation. Users' expectations can be mismatched by the AI's inconsistent responses, challenging their SoA and prompting them to exercise agency to achieve desired outcomes. Aligning communication patterns enhances users' SoA and satisfaction with HAIC. Collaboration depends on users' expectations, influencing their acceptance of AI failures.

7.2.7. It is okay to fail, but not that much

The Fallible Agent imaginary refers to the understanding of AI assistants as being prone to errors and imperfections. This imaginary can invoke a critical and cautious approach to interactions with AI (cf. 6.2.7). Users feel frustrated when stopped from obtaining desired answers.

Expecting an error-prone AI means users know it can fail, but not necessarily every type of error. Charlie was surprised by an unexpected error; all the CAI's links were inaccessible, which hindered his task-solving. He felt frustrated as these broken links hindered his ability to fact-check the CAI's answers, reinforcing his understanding of its fallibility. Fact-checking allows users to influence the HAIC and strengthens their SoA by confirming or refuting the CAI's answers (cf. 7.2.2 and 6.2.2). Due to the error prohibiting fact-checking, Charlie discovers a new dimension of the Fallible Agent: AI can be fallible in its links, not only its answers. This shows how users' imaginary and SoA are co-constructed dynamically. When users encounter limitations with AI, they adjust their imaginaries to capture the new experiences, but this affects their SoA in how they exercise agency. This demonstrates a cycle where a user's AI imaginary and perceived agency shape and impact each other throughout the user's interaction with the AI.

The Fallible Agent imaginary can influence users' recognition of fallibility and verification strategies to assess the CAI. The recognition of fallibility is challenged when the CAI provides overconfident, assertive answers. Eli doubted his knowledge due to the CAI's certainty. "Yes, I just needed to be sure, but it was also... [Eli finds the answer] yes I know. It can't," (p. 225) Eli commented after fact-checking the CAI's claims. The CAI's assertive response raises doubts among participants about their knowledge, especially when there is a disagreement. The participants' broad and complex technical knowledge (cf. 5) suggests they cannot remember everything exactly. When met with the CAI's overconfidence and opacity, the participants become doubtful, and their Fallible agent is challenged about how imperfect the CAI is. The participants deploy fact-checking verification strategies to exercise their agency and regain certainty and control. If users are to trust an AI system, it must rely on explainability and transparency in failure, so that users can easily identify if it is wrong and why. If users can provide feedback to the AI in cases of errors, they can develop a clearer mental model of AI and increase their trust in the system (Böckle et al., 2021). In this instance, the opacity of the CAI hinders

explainability and transparency, which diminishes their trust and challenges their imaginary rather than adjusting it. The Fallible Agent fosters verification strategies as an exercise of agency and critical behaviour, as participants understand the CAI to make mistakes, but are challenged by the CAI's opacity and overconfidence.

The Fallible Agent imaginary is challenged when new errors arise, or the AI's opacity causes doubt, leading to a weakened SoA in the users. In such cases, if possible, the users employ fact-checking due to AI's overconfidence and their broad knowledge of the documentation. Looking at all the imaginaries and their relation to participants' SoA, the findings suggest that three factors are crucial to the relation, which will be discussed in the following section.

7.3. Alignment in Expectations, Satisfaction and Communication

Insights into users' mental models, or imaginaries, and their SoA in HAIC reveal three recurring factors: expectations, communication, and satisfaction. These factors are vital for understanding the mutual shaping between users' SoA and imaginaries. This section elaborates on the crucial role of these factors in the correlation between AI imaginaries and SoA.

7.3.1. Expectations

Users' expectations of AI assistants are crucial to the relationship between AI imaginaries and SoA. A user's mental model of AI includes their understanding, attitude, and expectations, which shape their interactions with AI (Ngo, 2022; Schellewald, 2022). A user's expectations dictate how they think the AI should perform. When the expectations align with AI outcomes, users experience greater control and engagement. For example, with the Learning Entity imaginary, some participants expected improvement in the CAI over time, which made them influence the AI with their agency through mistake correction. Their expectations, based on the Learning Entity, guided how they exercised their agency in interaction with the CAI, with the hope of having their expectations met.

When user expectations are unmet, it can cause frustration and weakened SoA. AI chatbots often fail to meet users' expectations regarding trust, privacy, and usefulness (Janssen et al., 2017). The Personal Assistant and Super-computer imaginaries showed situations where users expected personalised communication or extraordinary computational power (cf. 7.2.4 and 7.2.5). The participant felt disappointed and diminished in their SoA when their expectations did not align with the CAI's actual capabilities. This is due to the imbalanced expectations and AI capabilities that cause frustrations and challenges for the HAIC (Janssen et al., 2021). However, findings suggest that ongoing use of AI can help align expectations and adjust mental models to AI's real capabilities.

Managing expectations is key to establishing a successful HAIC. As Glass et al. (2008) stated, "When describing their interactions with the system that were confusing or frustrating, or times when they considered abandoning the system, almost every participant mentioned expectation mismatches of some kind." (p. 232). This resonates with the findings that aligned expectations are necessary for a strong SoA and effective HAIC. Misaligned expectations can stem from a limited understanding of the AI system and its ability to adapt to user preferences (Glass et al., 2008). Findings indicate that mismatches in expectations can prompt users to exert their agency, allowing them to feel more in control of the HAIC. To avoid mismatch in HAIC, clarifying system functionality, input, and fallibility can help users adjust their mental model, fostering AI assistant user adoption (Kore, 2022). Aligning expectations is crucial in calibrating perceptions to reality, thereby enhancing the user experience and adoption.

Aligning users' expectations with AI performance is vital for collaboration. This alignment depends on users' perceptions of the AI, which can create high expectations and affect their perceived agency. Ongoing use and adjustment of mental models can align expectations over time. Adjusting imaginaries to reality also plays a part in the second factor, communication.

7.3.2. Communication

Effective communication is found to be vital for the user's SoA and imaginary for the AI. Contextual and clear communication can enhance the user's satisfaction and experience with the AI. Users exercise their agency in communicating with the AI and, in doing so, construct an understanding of how the AI communicates.

For some participants, the CAI is understood as a Communicative Partner, aiding the participants in how they converse with the CAI (cf. 7.2.6). The Communicative Partner imaginary shows how users, by providing specific prompts and context, establish a communicative pattern for the CAI, creating a framework for collaboration. This communication enables users to exercise their agency and tailor the AI to their individual preferences. Thus, users' perceptions of AI communication shape their interactions with AI assistants. Literature suggested that effective HAIC hinges on the clarity and ease of use of communication methods (Fragiadakis et al., 2024). When these methods align, they foster information exchange and mutual understanding. In short, the participants' communication methods are ways to exert their agency and stem from their imaginary with an expected communication pattern. For example, since AI lacks common-sense knowledge, users must provide context-specific information in their prompts (Shin, 2023), necessitating adjustments to their communication accordingly. The participants' imaginary of the CAI's communication pattern influences what contextual information they provide and how they expect the CAI to answer. Communication is a crucial factor in the relation between users' behaviour, imaginary and SoA. It highlights the importance of aligned communication methods between users and AI, enabling users to influence the AI through their agency and understand the AI's communication patterns.

If the communication is unaligned, it creates frustration and weakens users' SoA. When users feel they cannot influence the AI to reach their goals, they feel out of control and disengaged. As noted in Personal Potential (cf. 7.2.4), expectations for personalised communication impact users' SoA and work performance. An example is when Drew

struggled to complete his task due to excessive information and felt that the CAI had not adequately addressed his inquiries. The disconnect between Drew's question and the CAI's responses diminished his SoA. Misalignment in communication methods disrupts Drew's understanding of the CAI's functionality. Users interact based on their expectations of how the AI should communicate (Ngo, 2022); when the AI uses a different pattern, the collaboration is challenged. AI's opacity and black-box nature also hinder the option for seamless communication in HAIC, suggesting the need for careful consideration in designing AI for effortless communication (Puerta-Beldarrain et al., 2025). Consequently, users feel diminished in their SoA and misunderstood when the communication is misaligned in HAIC.

Comparing communication and expectations shows a close connection between the two. Users' expectations for how the AI works can also entail expectations for how the AI should communicate. However, the communication factor also entails the users' own communication patterns and the experienced communication between the user and the AI. Findings suggest that alignment in both expectations and communication can ensure the user's imaginary corresponds with the actual capabilities of the AI, and the user has a strong SoA in the collaboration.

In summary, communication is vital for understanding the connection between users' AI imaginaries and SoA in HAIC. Effective communication fosters collaborative interactions and helps users feel understood, while mismatches can cause frustration and diminish users' SoA. Moreover, communication and expectations are intertwined, providing insight into the relationship between AI imaginaries and Soa. The last factor, satisfaction, is also vital for interaction with AI assistants.

7.3.3. Satisfaction

A user's satisfaction is tied to their SoA, AI imaginaries, and the alignment of expectations and communication. The findings suggest that satisfaction refers to how well

the AI meets the user's needs and preferences, as well as the user's overall experience of the collaboration.

Findings showed that a satisfying HAIC is characterised by positive experiences that foster a positive attitude towards AI and higher engagement. If the user is not satisfied with the AI's performance, the user and the AI are unaligned. This unalignment can be in both expectations, communication, imaginaries, and SoA. For example, users who encounter errors or inaccuracies often feel frustrated and doubt the AI's capabilities, as seen with the Emotionless Agent and Fallible Agent (cf. 7.2.3 and 7.2.7). These experiences can cause dissatisfaction and disrupt the participants in their task-solving. Satisfaction is a crucial factor in keeping users engaged in HAIC (Diebel et al., 2025), and it can, along with acceptability, be increased through a strong SoA in the user (Pagliari et al., 2020).

Alignment between the user's imaginings and the AI's capabilities in terms of experiences and communication can lead to satisfaction. Satisfaction can, therefore, be viewed as a symbol of alignment in HAIC. When users are satisfied, they feel agentic and influential in their interactions with the AI, and their mental model aligns with reality. The three factors have been analysed based on the findings of AI imaginaries and users' SoA; however, they should be considered in terms of their empirical nature and future research.

7.3.4. Interpreting the Role of Expectations, Communication & Satisfaction

The three factors — expectations, communication, and satisfaction — are general tendencies that affect the correlation between imaginaries and SoA. For this case study, the three factors form pathways to understand how the users' imaginaries and SoA relate to each other. These factors highlight situations of misalignment between imaginaries and AI capabilities and of weakened or strengthened SoA. However, they should be considered in light of their contribution to the thesis and empirical anchoring.

As a means of understanding users' imaginaries and SoA in HAIC, the factors can be seen as a help to the theoretical framework. They helped identify how imaginaries,

SoA, and the user experience correlate by examining one aspect at a time but with a general perspective. The lack of theoretical support for the three identified factors is a noticeable liability. They were discovered during analysis, but without a theoretical anchoring in the framework of algorithmic imaginaries and SoA. These factors are more empirical findings than theoretical constructs. This necessitates more precise framing and argumentation for the factors based on existing literature.

The three factors are thus contextually dependent and shaped by users' imaginaries and SoA. They support the dynamic mutual shaping by showing the different aspects in which the two can influence each other. The alignment of the three factors significantly mediates the correlation between imaginaries and SoA. From the thesis's interdisciplinary perspective, this underscores how AI is a sociotechnical construct that enters an agentic relation with users in HAIC. In this relationship, users' mental models guide how they interact with the AI and are reshaped by the interaction. Effective HAIC not only depend on technical performance, but also on social and personal dynamics that shape users' engagement and experience.

In addition to the three factors, trust was a recurring factor in understanding AI imaginaries and SoA. Users who lack trust in AI are less likely to use it and often have worse experiences (Janssen et al., 2017). Literature emphasises the importance of trust in shaping user perceptions and experiences of AI (Wang, 2023; Kore, 2022; Afroogh et al., 2024). However, due to the scope of this thesis, a comprehensive coverage of trust is not feasible, so it is deprioritised in favour of the other three factors. This mention aims to acknowledge the validity of trust and encourage future research on its role in the correlation between user imaginaries and users' experienced agency.

This discussion emphasised three factors—expectations, communication, and satisfaction—that influence users' imaginaries and SoA in human-AI interactions. These factors provided insights into attitudes toward AI and the strengths or challenges in SoA but lack theoretical support and should be regarded as empirical findings. They promoted

a user-centric view, highlighting the socio-technical nature of AI and the interplay between imaginaries and SoA.

7.4. Summary of Agency in HAIC

The analysis compared the constructed AI imaginaries from Chapter 6 with users' behaviour and interactions during P2 to identify how their SoA relates to their imaginaries.

Findings indicated that AI imaginaries provide a framework for users' behaviours in AI interactions. When imaginaries align with reality, participants experience a strong SoA as their interaction leads to the desired outcomes. Unexpected results, accuracies or errors can challenge the participants' imaginaries and lead to a diminished SoA in the participant. Therefore, participants may decide to influence the CAI and exercise their agency to regain control in the HAIC. This analysis suggested that a user's AI imaginary and SoA mutually shape each other during interactions and evolve together as the user experiences the AI's responses. The findings should be considered as insights from a contextually dependent pilot study, which will be explained further in 8.4

The findings identified three factors influencing users' imaginaries and SoA: expectations, communication, and satisfaction. Misalignment among these factors challenges imaginaries or SoA, while alignment enhances the user-AI collaboration and users' experiences. Aligned expectations and communication lead to satisfaction, defined as a positive experience with AI. These factors are contextually dependent and form a pathway to understand aspects of the relationship between user imaginaries and SoA. The findings require scrutiny regarding nuances and overlooked perspectives before concluding the overall thesis.

8. Discussion of findings and contribution

The findings highlighted an interesting mutual shaping between the users' imaginaries and their SoA. However, these findings should be considered in terms of nuances and critical perspectives. This chapter will discuss the following perspectives.

- The mutual shaping of imaginaries and SoA
- The role of learning and gaining experience with AI.
- The limitations of accessing inner thoughts
- The practical and theoretical contributions of the thesis.

Each perspective is discussed in relation to its impact on the findings, the choices made throughout the analysis, and how future research can address these perspectives.

8.1. Mutual shaping of imaginaries and SoA

The findings consistently indicated a correlation between AI imaginaries and SoA that is mutually shaping and co-constructed. At its essence, the participants' constructed understanding of the CAI is influenced by and influences their felt and perceived agency in HAIC. For instance, Alex exercises his agency through an act of working around the CAI's regulations because he understands the CAI as having no moral compass or feelings (cf. 7.2.3). As such, he does not believe the CAI will be sad or angry when he circumvents its topic regulations. When he succeeds in influencing the CAI to reach his desired outcome, his understanding of the CAI as an Emotionless Agent is reinforced. Another example is how Drew initially felt a strong SoA as he understood the CAI to be learning from its mistakes and their interactions, as per the Learning Entity imaginary. Later, as he lacked proof of the learning development, he became more doubtful and weary, leading to his SoA diminishing (cf. 7.2.1). His imaginary faltered as he interacted more with the CAI, which impacted his SoA as felt he had no influence on the HAIC.

These examples and the findings suggest that the mutual shaping correlation resonates with the Critical Algorithmic Studies view of an algorithm as a socio-technical construct capable of affecting users (Seaver, 2017). The mutual shaping between imaginaries and SoA highlights the agentic influence that AI, as algorithmic systems, can have on users when the two interact. Similarly, it demonstrates the agentic behaviour users take to influence the AI (Kapsch, 2022) and how that behaviour stems from the user's understanding of the AI's workings (Ngo, 2022; Schellewald, 2022). As such, the correlation reveals a significant connection between how users understand AI and how it affects their felt agency in interactions with it.

Across the imaginaries, it is shown how participants' imaginaries influence their interaction with the AI. The participants' experiences with the CAI, in terms of accuracy, communication and performance, feed back into the correlation between their understandings and felt agency. This dynamic supports the idea of adaptive interaction, as users continuously try to understand and adapt accordingly with an AI throughout their interactions with it (Kang & Lou, 2022). When implementing AI in the workplace, it is thus recommended to design for the evolution of user understanding and provide users with options for exercising agency. For example, ensuring links work (cf. 7.2.7), feedback options (Böckle et al., 2021) or explainability and transparency in AI responses (Pagliari et al., 2022; Liu, 2021), meaning design or implications that support the dynamic correlation. Future research could explore further how design options impact the users' evolving co-construction of their imaginaries and SoA throughout interactions with AI. The mutual shaping dynamic is closely related to the role of learning and gaining experience with AI

8.2. Role of learning and experiences

The mutual shaping of imaginaries and SoA, along with participants' varying experiences with CAI, demonstrated the importance of learning curves and experiences in effective HAIC. Initial interactions tend to be less effective, but collaboration improves as

users and AI align. Continued user interaction is necessary for aligning communication and validating effectively. A successful HAIC requires specific human skills that users must develop beforehand or during collaboration to achieve better performance (Giordano et al., 2024). Ineffective HAIC is often attributed to human error in communication; however, a human-centred AI entails AI learning to communicate with users, not vice versa (Shin, 2023, pp. 182-183). This puts a demand for common-sense knowledge in AI, leveraging the expected skills in the users, which has caused difficulties among the participants.

The need for these skills underscores the correlation between imaginaries and SoA for the participants' experienced HAIC. Misalignment between the imaginary and reality can reduce SoA, as users' expectations do not align with reality and overlook their role in the partnership. Findings indicated that when users cannot see a clear connection between questions and answers or encounter unexpected scenarios, they struggle to influence the AI for better alignment. Learning development in HAIC is highlighted by Yu et al. (2024), who state, "We believe that the SoA dynamically changes in an HMI system, because the operator's feeling changes, their experience/knowledge increases, and their learning ability is improved with the progressive use of the system" (p. 5). SoA's dynamic nature is influenced by users' learning, feelings, and experiences. SoA evolves as users gain experience and evolve their understanding of the AI. Future research could explore further how users' learning curves and experiences help adjust their imaginaries to reality, affecting their SoA. The very act of accessing SoA and users' inner thoughts is crucial to discuss in relation to the findings' nature and validity.

8.3. Limitations of accessing inner thoughts

Investigating the SoA is challenging due to numerous factors affecting sensation. Relying on external agency through user reactions means that the data reflect the participants' emotional reports of the SoA (cf. 2.4). Accessing precise felt and perceived

agency is difficult; therefore, the findings are based on statements and reactions. A potential downside of this choice is that SoA varies in user differences such as trust in the system, personality, and understanding (Yu et al., 2024, p. 8). A sufficiently large sample size can mitigate this subjective variation; however, with the project's limited resources (cf. 4.7), the subjectivity may have influenced the findings.

Because the SoA is measured explicitly, the participants' understanding of SoA may not align with the author's theoretical understanding of SoA. The participant may instead have explained their interpretation of being in control. A sense of control can be seen as a fundamental experience that, along with the experience of intentional causation and the sense of initiation, constitutes a person's SoA. In itself, the sense of control can also be researched as a compound of basic experiences (Pacherie, 2007). This thesis has seen control as a part of a person's SoA; therefore, the two words are used somewhat interchangeably and consistently. However, the difference and relation between agency and control are important liabilities to consider when formulating and phrasing questions in this theoretical framework. However, the author did not notice the liability until the analysis and missed the opportunity to ask further about the participants' idea of control. Since SoA is a theoretical construct in psychology, asking the participants explicitly about their "sense of agency" may lead to confusion. If the author explained SoA to the participants, she may have biased their experiences and opinions. In retrospect, rather than asking about the participants' feelings of control, it would be more accurate to ask them to judge how much they felt their actions had caused the outcome (Moore, 2016). Changing the focus from the term "control" to the cause-and-effect relation in SoA. Further research could work on creating a more concise prompting schematic to help others apply the thesis's proposed framework in a feasible but agentic-focused manner. The focus on users' emotional report of SoA is due to the challenge of accessing users' inner thoughts.

By applying the theory of algorithmic imaginaries, the study employs a phenomenological paradigm to investigate phenomena despite not having direct access (p. 14, section 2.2). Phenomenology is focused on the "how" of things, meaning how objects appear, rather than how they truly are (Zahavi, 2019). As such, the findings highlight how AI assistants present themselves to participants, rather than how they are designed or function. While the theory has proven beneficial in identifying participants' imaginaries and SoA, the findings are heavily contextually dependent and reliant on the participants conveying their experiences.

The project employed a think-aloud approach to understand users' SoA in the cognitive walkthrough. However, this approach complicates the translation of thoughts into sentences, necessary for capturing the user's SoA. By requiring the user to convert unstructured thoughts into grammatically structured sentences, the user's thought process is disrupted in its natural flow (Charters, 2003). The very act of verbalisation can change the way users think. This can be mitigated by careful consideration of triangulation and interpretation methods (Charters, 2003). Although the thesis employed other methods of data collection, it poses a vital challenge for the proposed theoretical framework. By combining SoA and algorithmic imaginaries, the two complement each other to create a more comprehensive and stronger framework for accessing users' inner thoughts. The thesis should be viewed as a pilot study establishing a link between SoA and user imaginaries in HAIC. Therefore, future research is encouraged to explore the impact of explicit and implicit measurement of external agency on the understanding of SoA. The challenges and limitations do not undermine the valuable contributions made in the thesis.

8.4. Practical and theoretical contributions

The findings of this study make contributions of both a theoretical and a practical nature. The thesis's contributions include:

- Theoretical framework and methodology for imaginaries and SoA.

- Relevant factors impacting HAIC in the workplace.

The theoretical framework, which combines imaginaries and SoA, effectively identifies users' understandings of AI assistants and their perceived agency in interactions. It enhanced an understanding of users' conceptualisations through Bucher's algorithmic imaginaries, while emphasising the agentic relationship between users and AI through SoA. As such, the framework updated Bucher's theory to reflect current situations of advancements in HAIC. The theoretical framework made its contribution through the use of ethnographic and active participation methodologies. The methodology focused on creating a space for users to articulate their understandings and reflect on their felt agency. The thesis showcased the potential of in-situ active participation methodology through witnessing, semi-structured interviews, and cognitive walkthroughs with a think-aloud approach. This methodology provided insights into users' views of AI, their behaviour, and thoughts during human-AI interactions. Participants reflected on their real-time interactions with AI while engaging with the technology, allowing the author to capture natural reactions and compare them to articulated understandings. However, these methods were limited by users' interpretation and verbalisation of experiences, which can be influenced by various subjective factors (cf. 8.3). Furthermore, the novel methodology requires further refinement and evaluation; nonetheless, as a pilot study, the thesis illustrates the benefits of a combined methodology and an active participation focus.

The thesis's practical contributions entail insights into how to foster a successful and user-centric HAIC in the workplace. The findings illuminated the importance of mental models, agency, and alignment in expectations, communication, and satisfaction for effective HAIC. Companies should consider these factors when designing, implementing and evaluating AI assistants. Successful HAIC is neither given nor instant but requires alignment and constant readjustment, meaning that users must utilise the AI assistant continuously (cf. 8.2). The findings also demonstrated that skills and learning curves play a crucial role in alignment, suggesting that companies should focus on skill

development and provide effective feedback options in the AI design. The author presented the findings and recommendations to Kamstrup as part of the collaboration. This presentation is omitted due to the thesis's academic focus, but is available on the author's webpage: [Fransgaard Portfolio | Personal | Aarhus, Denmark](#). The thesis will conclude with a last reflection on and summary of the findings and insights.

9. Concluding thoughts

This master's thesis examined what understandings users construct about AI assistants and how these understandings affect users' perceived agency. The aim was to investigate how AI impacts users in HAIC in response to the increasing adoption of AI assistants in the workplace. The findings showed how the participants constructed seven distinct AI imaginaries that significantly impacted their perceived agency in HAIC. The Data-Driven System, Super-computer and Learning Entity imaginaries highlighted users' technical understanding of the CAI. The Communicative Partner and Personal Assistant imaginaries centred on the interactional aspect of CAI. The Fallible Agent and Emotionless Agent showed the ethical and sensitive dimension of CAI. The analysis revealed a dynamic, mutually shaping relationship between AI imaginaries and SoA, which evolves as the user interacts with the AI. A user's imaginary can impact their SoA, leading them to exercise their agency in behaviours to regain control of the collaboration. A strong SoA entails the user feeling influential and productive in their HAIC. The relationship is mediated by three factors: expectations, communication and satisfaction. The factors are pathways for understanding the correlation between imaginaries and agency. Alignment in the factors is often connected to an alignment between the users' imaginaries and AI's capabilities, possibly leading to a strong SoA in the user.

The theoretical framework extended Bucher's algorithmic imaginaries through the Sense of agency and adapted it to the contemporary situation by providing a novel perspective on the agentic relationship between users and AI. The framework enabled the

examination of user-AI interactions by highlighting the conceptual mental models as the foundation for how users exercise their agency. The ethnographic and participatory methodology demonstrated how combining interviews and cognitive walkthroughs can reveal the users' articulated imaginaries and connect them to their in-situ reflections on agency in interactions with an AI assistant. The interdisciplinary approach to a case study at Kamstrup has offered a contextual and empirical understanding of users' behaviour in HAIC while remaining critical and analytical.

The findings suggested that users' understanding and felt agency can inform user-centric AI design in an organisational setting by ensuring users feel influential in their collaboration. Understanding users' imaginaries and their exercise of agency can guide the design process in developing transparent and collaborative AI assistants. The thesis was limited to a single case study, and it faced practical challenges, including the researcher's capabilities, the availability of resources, and the delay in AI implementation at Kamstrup. While the findings were context-specific, they offered valuable insights and contextual trends regarding AI's impact from a user perspective.

Future research of a longitudinal study could show how user understandings and agency evolve over time, examining the role of learning experiences and the readjustment of mental models. Otherwise, exploring the nuances of the correlation between imaginaries and SoA in further detail would be beneficial to investigate the mediation of the three factors more closely. The thesis encourages other academics to expand research on user understandings and agency to new contexts and cases, thereby enhancing the work on the impact of AI. As AI assistants integrate into daily life, including workplaces, understanding user perceptions and interactions with AI becomes a crucial concern. The thesis emphasises the need for human-centric AI design that respects the dynamic relationship between user understanding and agency, influencing how users adopt AI in their work practices. Understanding this dynamic is essential for designing AI systems that empower users in their collaborative work with AI.

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