PERCEPTIONS AND TRUST OF AI AMONG HEALTH CARE PROFESSIONALS

A Mixed-Methods Study Before and After a Pilot Interruption

Teemu Koivula

Supervisor:
Panagiotis Bamidis, Professor of Medical Physics, Informatics and Medical Education, and Director of the Lab of Medical Physics and Digital Innovation in the School of Medicine at the Aristotle University of Thessaloniki, Greece

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Acknowledgements

I would like to express my deepest gratitude to everyone who supported me throughout this thesis journey. First, I extend my sincere thanks to my supervisor, Professor Panagiotis Bamidis, for his guidance, expertise, and encouragement. His insightful feedback and commitment to research excellence were invaluable in shaping this work. My appreciation goes to the entire research group for their collaboration, discussions, support, encouragement, ideas, and companionship throughout this project.

Finally, I dedicate this thesis to my family. Your patience, belief in me, and unwavering support carried me through every stage of this journey. I am deeply grateful for your presence in my life.

Thank you all.

Abstract

Artificial intelligence (AI) is increasingly introduced into health care to improve efficiency, support decision-making, and reduce administrative burden. However, many AI projects stall before full implementation, and little is known about how such interruptions shape professionals' perceptions or trust. This study investigates health care professionals' perceptions of AI before implementation and examines how an unexpected pilot interruption influenced their views on organisational readiness, technological maturity, and institutional trust.

An explanatory sequential mixed-methods design was used. A pre-pilot survey (N = 75) captured baseline attitudes toward AI, understood here as structured evaluative perceptions. Quantitative analyses included descriptive statistics, group comparisons, and correlation analysis. Semi-structured thematic interviews (n = 6) followed and were analysed using theory-driven qualitative content analysis informed by sensemaking theory.

Survey results showed generally positive initial attitudes, especially among younger professionals and those with previous AI experience. Higher perceived AI competence strongly correlated with more favourable attitudes. Interview findings indicated that the pilot interruption did not substantially change technology-related attitudes. Instead, it triggered reinterpretations of organisational readiness, resource allocation, and the maturity of the technology. The interruption was interpreted as affecting institutional trust more than trust in the AI system itself, with participants linking the event to communication practices, timing, and broader organisational challenges.

The study suggests that interrupted implementations function as critical sensemaking events in which institutional trust becomes the primary object of re-evaluation, whereas attitudes toward AI remain comparatively stable. The findings highlight the importance of transparent communication, realistic expectations, and organisational preparedness when managing AI adoption.

Keywords: Artificial intelligence, Health care professionals, Interrupted implementation, Sensemaking, Technology Acceptance, Trust

JEL Classification: I18; O33

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Introduction

Health care systems are under continuous pressure to deliver high-quality and equitable services while managing increasing patient volumes, complex clinical information, and persistent workforce shortages. Routine tasks such as documentation, information retrieval, and compliance with guidelines consume substantial time and contribute to cognitive burden and workflow inefficiencies (Choudhury & Asan, 2022; Lambert et al., 2023). These pressures are well-known contributors to mental fatigue, cognitive overload, and reduced well-being among clinicians, as heavy documentation and regulatory demands place sustained cognitive strain on staff (Hudson et al., 2025; Zhao et al., 2025). At the same time, organisations operate under economic constraints and rising expectations for productivity and service quality, a pattern discussed both in general AI-in-healthcare literature (Kumar et al., 2023) and in Finnish public-sector analyses (Pulkkinen et al., 2025). Together, these conditions highlight the need for tools that support both operational efficiency and clinical decision-making in time-critical environments (Asan et al., 2020; Romero-Brufau et al., 2020).

Artificial intelligence (AI) has been explored as a potential response to these challenges. AI refers to technologies that enable machines to perform tasks typically requiring human intelligence, such as reasoning, learning, and interpreting natural language. An AI system, as defined in the EU Artificial Intelligence Act, is a machine-based system that operates with some autonomy, may adapt after deployment, and infers from input how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. (Regulation (EU) 2024/1689, 2024). In health care, AI is increasingly used to support decision-making in complex settings and has shown potential to improve diagnostic accuracy, enhance patient outcomes, and transform processes of prevention, diagnosis, and treatment (Kumar et al., 2023; Topol, 2019). Reviews identify rapid progress across diagnostics, decision support, predictive analytics, and service management, while also noting the need for stronger real-world evidence (Al Kuwaiti et al., 2023; Secinaro et al., 2021).

However, a critical knowledge gap remains. Most AI adoption research focuses on successful or ongoing implementations and assumes a relatively linear progression from introduction to use, even though many pilots fail to progress beyond early stages. Recent industry evidence suggests that up to 95% of generative AI pilots do not proceed beyond initial testing, according to an industry report by Challapally et al. (2025). Available research does not address how interruptions of AI pilots influence professionals' trust and expectations, or how professionals make sense of the interruption itself. Existing technology-acceptance frameworks such as TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003) primarily address adoption in contexts where users gain direct experience with a system.

Consequently, they offer limited guidance for situations in which implementation is interrupted, or hands-on use does not occur.

Interrupted implementations are analytically meaningful because they prompt sensemaking processes through which individuals interpret unexpected or ambiguous events to restore coherence (Weick, 1995; Weick et al., 2005). When professionals lack direct experience with a technology, they rely more heavily on organisational cues, communication, and contextual signals than on system performance. Prior research shows that under such conditions, institutional trust (confidence in the organisation's decision-making, governance, and preparedness) often becomes more salient than technology-level trust (Asan et al., 2020; Steerling et al., 2023; Sun & Medaglia, 2019). Interruptions may therefore shape perceptions not primarily by altering attitudes toward AI, but by influencing interpretations of organisational capability and commitment.

This study examines these issues in the context of an AI Assistant pilot conducted in two Finnish wellbeing services counties. The pilot aimed to support professionals with tasks such as information retrieval, assessment of care needs, and client guidance, and was positioned as an initiative within the national AI ecosystem for social and health services (AI Ecosystem in Social and Health Services, n.d.; Etelä-Savon hyvinvointialue & Keski-Suomen hyvinvointialue, 2024). The pilot was interrupted during the testing phase, before most professionals had the opportunity to use the system. As a result, the research focus shifted from understanding the influence of a successful pilot toward understanding how the interruption itself shaped professionals' interpretations of organisational readiness, technological maturity, and expectations regarding the use of AI.

To address these aims, the study employs an explanatory sequential mixed-methods design: a pre-pilot survey captures baseline attitudes and perceived AI competence, followed by thematic interviews exploring professionals' interpretations of the interruption. In this thesis, attitudes are conceptualised as evaluative perceptions formed before implementation, while the interview phase examines interpretive perceptions that arise when professionals make sense of the interruption. The study expects that health care professionals generally hold positive baseline attitudes toward AI and that the interruption influences institutional trust.

Microsoft Copilot was used to assist in language refinement and idea generation in accordance with institutional guidelines for responsible AI use.

Chapter 1 - Background

This chapter presents the context and theoretical foundation of the study. It begins with an overview of the AI Assistant Pilot Project to contextualise the empirical setting. It then synthesises determinants of AI adoption, drawing from established technology acceptance models and complementary literature on trust. Next, it reviews empirical research on health care professionals' perceptions of artificial intelligence. The chapter then introduces sensemaking theory as a lens for analysing how professionals interpret the unexpected interruption of the AI pilot. Finally, the last section summarises these perspectives into a coherent theoretical framework that connects baseline attitudes with interpretive responses to the pilot interruption.

1.1 The AI Assistant Pilot Project

The Ministry of Social Affairs and Health of Finland coordinates a National AI Ecosystem for social and health services. The ecosystem facilitates, enables, and funds AI uptake while aiming for safe, privacy-respecting service delivery (AI Ecosystem in Social and Health Services, n.d.). Within this ecosystem, DigiFinland launched ten AI pilot projects in 2025. In May 2025, the AI Assistant for Professionals Pilot Project was started in the Wellbeing Services County of Central Finland (Hyvaks) and in the Wellbeing Services County of South Savo (Eloisa). The work units participating in the pilot from Hyvaks were the unit of centralized assessment of care needs, the first-line unit for mental health and the substance abuse services, and the Joutsa health centre. The first-line customer guidance unit was participating from Eloisa.

The pilot aimed to examine how AI-assisted tools could support professional work and improve consistency in areas such as information and clinical guideline retrieval, assessment of care needs, and client guidance. Although the detailed use cases varied between the two wellbeing services counties, the basic issues of AI usage were the same. The technology was also expected to support both new and experienced professionals by helping them navigate extensive service pathways and organisational instructions. This was anticipated to contribute to reduced cognitive burden. In the longer term, the pilot was expected to support improvements in documentation practices and the overall quality of records (Etelä-Savon hyvinvointialue & Keski-Suomen hyvinvointialue, 2024).

The pilot was also framed as an initiative to explore AI's role in preventive services and client guidance, for example, through the provision of care summaries and descriptions of service chains. Across the planning material, AI was positioned as a tool that supports, rather than replaces, professional judgment. The expectation was not only to improve the efficiency and quality of work, but also to offer opportunities to modernise culture through technology while maintaining the humanity and professionalism of care.

The pilot was planned to run until the end of 2025, but it was interrupted during the testing phase in August 2025. As a result of the interruption, most professionals did not gain hands-on experience with an operational AI assistant. Understanding the intended functions and unrealised implementation of the pilot provides context for the adoption determinants discussed next.

1.2 Determinants of AI Adoption in Health Care

Adoption of AI in health care is shaped by determinants that influence how professionals perceive, interpret, and evaluate new technologies in their work. These determinants may originate from features of the technology or from organisational circumstances, but they become meaningful through how individual professionals assess their usefulness, usability, and relevance to daily practice.

Established technology acceptance models emphasise cognitive, experiential, and social factors that guide these evaluations, while health care settings highlight additional considerations such as workflow integration, professional autonomy, safety requirements, and perceptions of technological maturity. Trust is also an essential determinant because professionals must judge whether AI systems and the organisations deploying them are reliable and appropriate for clinical contexts. Together, these determinants provide the basis for understanding how professionals form expectations of AI prior to implementation and how these expectations shape willingness to use AI-assisted tools.

1.2.1 Technology Acceptance Frameworks

Technology acceptance research has traditionally emphasised the cognitive beliefs guiding individuals' decisions to adopt new systems. The Technology Acceptance Model (TAM) proposes that perceived usefulness and perceived ease of use shape attitudes toward use, which in turn influence behavioural intention (Davis et al., 1989; Holden & Karsh, 2010). Perceived usefulness refers to the belief that a system improves performance, and perceived ease of use refers to the belief that it requires minimal effort. Later extensions of TAM highlight that acceptance of digital technologies is also influenced by evaluative judgments related to uncertainty and potential negative outcomes (Featherman & Pavlou, 2003).

The Unified Theory of Acceptance and Use of Technology (UTAUT) complements TAM by identifying performance expectancy, effort expectancy, social influence, and facilitating conditions as additional determinants of behavioural intention and actual use (Venkatesh et al., 2003). Subsequent research has refined this framework by demonstrating that attitude also plays a central role in shaping behavioural intention and technology use (Dwivedi et al., 2019). Professionals' overall evaluations of AI, including trust, perceived benefits, and perceived risks, can strongly influence adoption. In health care settings, these constructs reflect expectations about work efficiency, cognitive demands, professional norms, and organisational support.

Performance-related expectancy constructs play a central role in shaping early perceptions of AI. In the acceptance frameworks, these expectations correspond to perceived usefulness in TAM and performance expectancy in UTAUT. They refer to beliefs that a technology can enhance work performance, decision quality, or efficiency. In clinical contexts, such expectations often relate to AI's potential to improve decision-making processes and reduce the cognitive load associated with documentation and information retrieval (Holden & Karsh, 2010; Topol, 2019). When professionals anticipate meaningful improvements in these domains, they are more likely to form favourable attitudes toward use (Davis et al., 1989; Venkatesh et al., 2003).

Effort-related expectations operate in parallel by capturing beliefs about usability, learnability, and interaction demands. These expectations correspond to perceived ease of use in TAM and effort expectancy in UTAUT (Davis et al., 1989; Venkatesh et al., 2003). Technologies seen as intuitive or well aligned with existing workflows tend to reduce perceived effort and strengthen positive attitudes even before implementation (Holden & Karsh, 2010). Conversely, systems perceived as complex or disruptive can increase anticipated effort and weaken intention to use.

Social influence, alongside performance and effort expectations, contributes to intention formation. Social influence refers to perceptions of colleagues, supervisors, or professional groups regarding the acceptability or desirability of AI use. Because clinical work is collective and norm-governed, signals from respected peers or organisational leaders can legitimise emerging technologies and reduce hesitation, particularly in early implementation phases. Acceptance research shows that social influence plays a stronger role when individuals have limited experience or when a technology is introduced in structured organisational settings (Dwivedi et al., 2019; Venkatesh et al., 2003).

Facilitating conditions form the structural dimension of adoption determinants and refer to the organisational and technical resources that support effective technology use. In the framework, facilitating conditions capture the extent to which individuals believe that the necessary infrastructure, support, and organisational readiness are in place to enable use (Dwivedi et al., 2019; Venkatesh et al., 2003). Evidence from health care technology research indicates that such organisational support is essential for transforming favourable beliefs into actual behaviour (Choudhury & Asan, 2022; Holden & Karsh, 2010). Conversely, weak structural support, insufficient integration, or unclear operational processes can prevent even positive expectations from leading to sustained use (Lambert et al., 2023; Romero-Brufau et al., 2020).

In health care settings, technology acceptance is further shaped by professional, workflow-related, and technological maturity considerations. Workflow fit is consistently identified as a critical condition for successful AI adoption. AI systems are often rejected when they introduce additional documentation tasks, disrupt established routines, or create misalignment with clinical information flows, even when their potential usefulness is recognised (Hassan et al., 2024; Lambert et al., 2023;

Romero-Brufau et al., 2020). Poor integration can increase cognitive workload or slow down coordination in time-critical settings (Choudhury & Asan, 2022; Petersson et al., 2022).

Relational and professional determinants also shape acceptance. Professionals may resist systems that appear to override their judgment, reduce autonomy, or obscure clinical reasoning (Ackerhans et al., 2024; Jones et al., 2023; Shonhe & Min, 2025). Conversely, adoption is facilitated when AI-assisted tools are framed and experienced as augmenting rather than replacing professional expertise (Doraiswamy et al., 2020; Topol, 2019).

Perceived technological maturity further influences adoption intentions. Immature, unstable, or insufficiently validated systems raise concerns about reliability and safety, which can override favourable beliefs about usefulness or ease of use (Asan et al., 2020; Steerling et al., 2023). Ethical and regulatory credibility also shape acceptance, particularly in European health care governed by strong data protection and accountability requirements (European Union 2016; Regulation EU 2024/1689).

The determinants outlined above provide the foundation for understanding the cognitive and organisational factors that shape early evaluations of AI. Beyond these determinants, trust plays a central role in health care AI adoption and therefore requires separate consideration.

1.2.2 Trust in the Context of AI Adoption in Health Care

Trust warrants separate consideration because it reflects professionals' willingness to rely on AI recommendations in situations that involve uncertainty, professional accountability, and patient safety. Prior research consistently identifies core qualities of AI systems, including reliability, accuracy, transparency, interpretability, and safety, as central influences on clinicians' readiness to rely on outputs generated by AI-based tools (Asan et al., 2020; Astobiza et al., 2025; Tun et al., 2025). These features shape trust beyond general attitudes toward technology adoption, since AI recommendations can affect clinical assessments, documentation quality, and decisions with direct implications for patient outcomes and organisational credibility (Jones et al., 2023; Mertz et al., 2025).

For these reasons, trust is widely understood as a fundamental determinant of AI adoption in health care. This study approaches trust in a two-level distinction presented in Figure 1.1. The distinction encompasses both technology-level trust in the system's technical qualities and institutional-level trust in the organisation responsible for introducing and governing the technology.

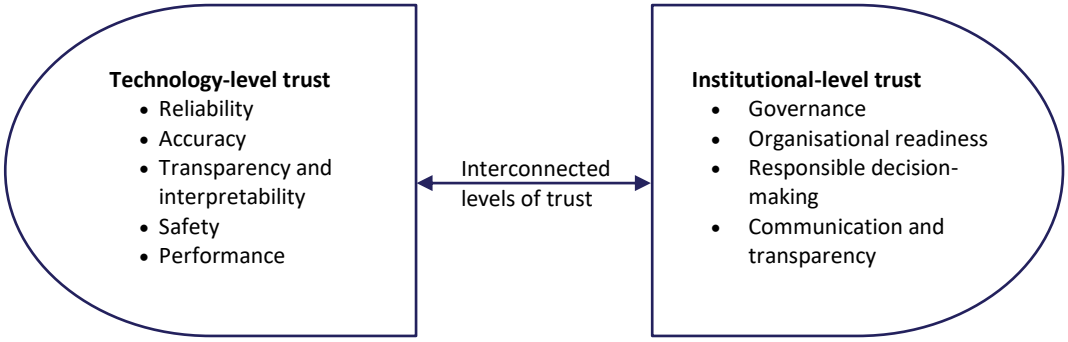


Figure 1.1 Conceptual Distinction Between Technology-Level and Institutional Trust.

Note. Source: Author's own elaboration.

At the technology level, professionals evaluate whether an AI system performs reliably and consistently, whether its outputs are accurate in the relevant clinical context, and whether they can understand or assess how the system arrived at its recommendations. Transparency and clarity in system behaviour support trust because they enable clinicians to judge whether the system's reasoning aligns with professional expectations and established clinical logic (Astobiza et al., 2025; Tun et al., 2025). Reviews repeatedly highlight that trust strengthens when AI systems offer stable performance, demonstrate adequate validation, and provide explanations or rationales that clinicians can interpret meaningfully (Secinaro et al., 2021; Tun et al., 2025). These characteristics reduce perceived risk and support professionals' willingness to rely on AI-assisted recommendations in contexts where decisions have significant clinical consequences.

Trust in AI systems develops through continuous interaction, feedback, and observation of system behaviour over time. Professionals adjust their trust as they encounter system behaviour, observe how well the system fits clinical workflows, and compare its suggestions with their own judgment and experience. Too much trust may lead to uncritical acceptance of AI output, while too little trust may result in overlooking potentially valuable insights. Trust calibration, understood as the process through which users adjust their trust in an AI system as they gain repeated interaction experience, is emphasised in recent work on human–AI collaboration (Daly, Hearn et al., 2025; Sagona et al., 2025). This dynamic view of trust aligns with foundational human-factors research, which conceptualises trust as a process that evolves as users learn to assess system reliability, predictability, and transparency over time (Lee & See, 2004).

Professional judgment and identity further shape technology-level trust. Research shows that clinicians trust AI tools more readily when the tools support, rather than constrain, their autonomy and expertise, and when the system's logic aligns with established professional reasoning (Ackerhans et al., 2024; Shonhe & Min, 2025). Conversely, trust may be weakened when AI systems appear to

override clinical judgment or when the underlying logic of the system remains obscure, even when performance is adequate. These findings highlight the relational nature of trust, where acceptance depends not only on system performance but also on how the system fits with clinicians' roles, professional identities, and expectations.

In addition to technology-level properties, trust depends strongly on the behaviour, readiness, and governance of the organisation responsible for introducing AI. When professionals have limited hands-on experience with a system, they cannot assess its performance directly and therefore rely more heavily on organisational signals. Institutional trust refers to confidence in the organisation's ability to introduce AI responsibly, including beliefs about governance structures, decision-making processes, communication quality, and organisational preparedness (Steerling et al., 2023; Wang et al., 2023). These factors become especially important in early stages of implementation or in circumstances where technological maturity is unclear.

Organisational communication plays a central role in shaping institutional trust. Clear justification for the introduction of AI, transparency in decision-making, and visible commitment to monitoring and oversight all contribute to positive expectations (Petersson et al., 2022). Likewise, adequate training, meaningful opportunities for engagement, and alignment with existing workflows support trust by demonstrating organisational readiness and responsibility (Astobiza et al., 2025). When these elements are lacking, uncertainties may increase, and trust may weaken, even when the technology itself is promising. Research on public-sector AI adoption suggests that professionals often evaluate organisational capability and governance before forming firm expectations about the system's usefulness or safety (Jöhnk et al., 2021; Sun & Medaglia, 2019).

Although technology-level trust and institutional trust can be analytically distinguished, they are closely interconnected in practice. Strong institutional trust may sustain positive expectations toward an unfamiliar AI system, whereas weak institutional trust can undermine willingness to adopt a system regardless of its technical performance (Astobiza et al., 2025; Wang et al., 2023). Because AI systems are often introduced gradually and early user experience may be limited, organisational signals related to governance clarity, communication, and responsible planning frequently precede and shape technology-level trust (Petersson et al., 2022; Steerling et al., 2023). These dynamics underscore that trust formation in health care AI must be understood within the broader organisational and professional context in which the technology is deployed.

1.3 Health Care Professionals' Perceptions of AI

Empirical research on health care professionals' perceptions of AI presents a pattern of cautious optimism. Across reviews and primary studies, professionals frequently recognise potential benefits related to efficiency, support for clinical reasoning, documentation, and care coordination (Ayorinde

et al., 2024; Chew & Achananuparp, 2022). These positive expectations often coexist with concerns about transparency, safety, accuracy, and the maturity of AI systems. Professionals commonly note uncertainty about how AI produces its outputs, how reliable these outputs are in specific clinical contexts, and how responsibility is shared when AI is integrated into decision-making (Ayorinde et al., 2024; Chew & Achananuparp, 2022).

Studies also show that demographic factors shape perceptions of AI. A national survey of geriatric health professionals in South Korea found that younger professionals reported higher technology acceptance and better AI knowledge, indicating a cohort effect in openness toward digital tools (Choi, 2023). Similar age-related patterns appear in international reviews, with younger staff consistently showing greater optimism and receptivity toward AI technologies (El Arab et al., 2025).

A large international synthesis of 72 empirical studies reports that perceptions are shaped by experiences at multiple levels of practice, including individual attitudes and competence, team norms, workflow integration, and wider organisational and regulatory conditions in hospital, primary, and specialist settings (Henzler et al., 2025). A qualitative meta-aggregation of studies from Europe, Asia, and North America identifies five recurring areas in professionals' accounts: expected benefits; implications for roles and workforce dynamics; effects on communication and interaction; technical and systemic challenges; and ethical, cultural, and regulatory concerns (Huotari et al., 2026).

Perceptions also vary across professional roles and care environments, although a broadly similar pattern emerges across studies. Nurses frequently emphasise the need for training and clarity about the capabilities and limits of AI and often describe AI as a potential means of reducing workload while maintaining professional judgement (Abuzaid et al., 2022). Survey findings from Germany likewise indicate that professionals may hold generally positive expectations despite limited technical knowledge, suggesting a gap between enthusiasm and conceptual mastery (Sommer et al., 2024). Among physicians, mixed-methods research reports both interest and scepticism, with more favourable attitudes observed among clinicians familiar with AI or engaged in related research (Heinrichs et al., 2025). A recent survey in the United States echoes this pattern, showing broadly positive expectations among physicians alongside limited understanding of AI principles or system behaviour (Gebauer & Eckert, 2024). Together, these studies suggest that while enthusiasm toward AI is common across roles, familiarity and competence play a central role in shaping perceptions.

Perceived usefulness of AI is also closely linked to clinical context and workflow fit. Across acute care, diagnostic imaging, outpatient settings, and chronic care management, some studies describe AI outputs as clinically relevant and supportive, whereas others report that recommendations are insufficiently contextualised or poorly aligned with local practice, diminishing perceived value (Ayorinde et al., 2024). Among hospital-based staff in secondary care, acceptance tends to improve when systems reduce cognitive burden and integrate smoothly into everyday information flows, and

it weakens when tools add documentation steps or disrupt established routines (Lambert et al., 2023). These findings highlight the importance of workflow integration as a determinant of favourable perceptions.

Limited preparedness is a consistent theme across empirical studies. Professionals frequently report low levels of AI knowledge and call for structured training and clear guidance to support confident and safe use in practice, a pattern documented across inpatient and outpatient environments as well as in nursing education (Abuzaid et al., 2022; Chew & Achananuparp, 2022; Swan, 2021). The German nursing survey further suggests that interest in AI often exceeds competence, underscoring the need for early exposure and hands-on training to calibrate expectations and build realistic, informed perceptions (Sommer et al., 2024). Reviews similarly show that digital literacy, computer skills, and familiarity with emerging technologies strongly shape readiness for AI, with lower digital confidence associated with hesitation and anxiety (El Arab et al., 2025).

Trust emerges as a central element in healthcare professionals' perceptions of AI, particularly in clinical decision support systems such as those studied in the UK. Clinicians emphasise interpretability, transparency, validation, and accountability as preconditions for trusting recommendations and identify legal liability as a salient dimension of trust in real clinical decisions (Jones et al., 2023). A systematic review of trust in AI-based decision support across clinical specialities reports that transparency, familiarity and training, usability and workflow integration, clinical reliability, evidence of validation, ethical clarity, and the ability for clinicians to retain control are prominent influences on trust formation (Tun et al., 2025). Additional clinician-focused analyses highlight perceived risks around bias and explainability and the need to safeguard professional competence within human-AI collaboration (Asan et al., 2020).

When professionals have limited direct experience with AI, organisational signals play an important role in shaping perceptions. Commitments to responsible AI principles, visible communication, and opportunities for engagement influence how safe or trustworthy systems are perceived to be. Evidence indicates that signals relating to autonomy, beneficence, explainability, justice, and non-maleficence strengthen favourable perceptions, though positive effects may weaken when professionals experience increased workload or technological burden (Wang et al., 2023).

Early experiences with AI in routine practice also shape perceptions. In a staff survey at the UK NHS trust, professionals described AI as potentially useful but also raised significant concerns about privacy, safety, and the implications of limited understanding, illustrating the coexistence of enthusiasm and apprehension during early implementation (Castagno & Khalifa, 2020). Across clinical environments, perceptions tend to be most positive when recommendations are clinically relevant, validated, and clearly aligned with local workflows and professional goals (Lambert et al., 2023).

Across studies, the overall pattern is one of conditional positivity. Health care professionals are generally open to the idea of AI and recognise its potential benefits, yet maintain clear expectations regarding reliability, interpretability, accountability, training, and workflow compatibility. These perceptions are shaped by personal competence, everyday clinical experiences, organisational communication, and broader ethical and regulatory contexts (Ayorinde et al., 2024; Chew & Achananuparp, 2022).

1.4 Interpreting Interrupted AI Implementations

Technology acceptance models offer structured explanations for how professionals form expectations about new technologies, but their explanatory power becomes limited when implementation processes do not unfold as planned. In health care organisations, unexpected events trigger sensemaking processes in which individuals interpret ambiguous situations by drawing on experience, contextual cues, and organisational norms (Brown et al., 2014; Weick, 1995; Weick et al., 2005).

Sensemaking therefore complements the more static determinants emphasised in acceptance frameworks. When an implementation is interrupted, professionals try to understand why it occurred, what it reveals about organisational capability, and how it may affect their work. Research on technology adoption increasingly highlights that interpretive work begins before any hands-on use, as individuals form initial perceptions, symbolic associations, and expectations long before direct interaction with a system (Seligman, 2006).

1.4.1 Sensemaking in the Absence of Hands-On Experience

As professionals engage in sensemaking, they evaluate not only the anticipated benefits but also constraints and uncertainties surrounding the technology. Their assessments do not rely solely on cognitive evaluations such as perceived usefulness or effort expectancy, particularly when hands-on experience is absent. In these situations, organisational communication and contextual cues become central sources of meaning. Professionals use these signals to interpret both the technology and the institutional environment in which it is introduced, postponed, or withdrawn. Research shows that communication quality and governance signals strongly influence how unfamiliar technologies are interpreted in early or disrupted implementation contexts (Petersson et al., 2022; Steerling et al., 2023).

Within this interpretive context, limitations take on meanings that extend beyond their technical properties. Uncertainties concerning reliability, boundary conditions, and technological maturity become cues through which professionals evaluate organisational preparedness and the perceived safety of adoption. According to a preprint by Übellacker (2025), such uncertainties may even be

interpreted as indicators of readiness, insofar as individuals use perceived limitations to assess whether an organisation is capable of responsibly implementing emerging technologies. This view aligns with broader research demonstrating that implementation context, governance clarity, and professional expectations strongly influence how limitations are understood in practice (Brown et al., 2014; Sun & Medaglia, 2019). Seligman's (2006) account further reinforces this perspective by illustrating how individuals classify what they notice through extracted cues, drawing on familiar frames and plausible interpretations, particularly when concrete system experience is absent.

1.4.2 Organisational Communication and Institutional Trust

Implementation interruptions foreground questions of organisational competence. Professionals scrutinise communication quality, planning coherence, and the adequacy of organisational support (Petersson et al., 2022; Steerling et al., 2023). Sudden changes, unclear rationales, or limited transparency can be interpreted as signals of insufficient readiness. When hands-on experience is lacking, organisational signals may become more influential than beliefs about the technology itself. Research shows that perceived readiness, governance clarity, and implementation competence strongly shape interpretations under uncertain conditions (Jöhnk et al., 2021; Niemelä et al., 2025).

At this point, the distinction introduced earlier between technology-level trust and institutional trust becomes important. Technology-level trust is shaped by pre-existing attitudes and expectations, whereas institutional trust reflects how professionals evaluate the organisation's decisions, governance practices, and communication during the interruption. When professionals have no opportunity for direct experience with an AI system, institutional trust becomes the primary lens through which the interruption is interpreted. This helps explain why interruptions often influence confidence in organisational decision making more strongly than underlying attitudes toward AI (Steerling et al., 2023; Sun & Medaglia, 2019). Research on AI implementation emphasises that transparency, clear justification, and visible governance responsibility help sustain institutional trust during periods of uncertainty, while ambiguous explanations can weaken confidence (Petersson et al., 2022; Steerling et al., 2023).

1.4.3 Interruptions as Evaluative Signals of Organisational Capability

Interruptions may also prompt professionals to reconsider the purpose and legitimacy of the project. They may question whether the interruption stems from technical limitations, financial pressures, organisational priorities, or broader strategic considerations. AI initiatives require coordinated resources and sustained organisational commitment. When implementation is interrupted, professionals may begin to question the long-term feasibility of the project and the organisation's capability to support AI in practice (Lambert et al., 2023; Niemelä et al., 2025). These

interpretations extend beyond the specific pilot context and can shape broader expectations about future innovation efforts.

Interruptions form a distinct evaluative context within the adoption process. Acceptance frameworks often assume a linear progression from introduction to use. When implementation ends prematurely, however, professionals cannot rely on experiential learning. Instead, they interpret the interruption through prior expectations, organisational communication, and the symbolic meaning of the event (Weick, 1995; Weick et al., 2005). Seligman's sensemaking perspective reinforces this by showing that adoption is not a single decision but an ongoing sequence of sensemaking cycles through which cues are interpreted, identities are reconstructed, and plausible understandings are formed (Seligman, 2006). In this context, an interruption becomes an event through which professionals assess risk, organisational readiness, and the credibility of broader AI initiatives (Asan et al., 2020; Daly, Wiewiora et al., 2025).

Together, these dynamics illustrate why implementation interruptions require dedicated analysis. Professionals' responses originate not only from acceptance determinants but also from interpretations of organisational behaviour, communication quality, and institutional reliability. The interrupted pilot in this study provides a distinctive context for examining how expectations, trust, and sensemaking interact when implementation deviates from what professionals anticipated. Expectations had been created, responsibilities assigned, and the pilot linked to broader regional AI strategies. Understanding this context clarifies how the interruption shaped perceptions and trust and why it offers a meaningful opportunity to study sensemaking during a disrupted implementation.

1.5 Summary of the Theoretical Framework

This thesis examines health care professionals' perceptions of AI through a multilevel theoretical framework that integrates literature on technology acceptance and trust, and sensemaking theory. Together, these perspectives explain both the evaluative judgments formed before implementation and the interpretive responses that arise when an implementation process is interrupted.

Technology acceptance theories describe how early expectations about AI are formed. These expectations relate to perceived usefulness, ease of use, performance and effort expectancy, social influence, and facilitating conditions. In health care settings, these determinants are further shaped by workflow fit, professional autonomy, technological maturity, and regulatory considerations. In this thesis, these early expectations are operationalised as attitudes toward AI. Attitudes are understood as structured evaluative perceptions that reflect professionals' pre-implementation assessments of the potential benefits, challenges, and trustworthiness of AI. They represent one dimension of perception that is measurable before professionals have direct experience with the technology.

Trust constitutes a second key component of the framework. Technology level trust refers to confidence in the reliability, accuracy, and safety of AI systems, while institutional trust concerns confidence in organisational governance, readiness, communication, and decision making. Technology level trust forms part of evaluative attitudes because several attitude items reflect judgments about reliability and risk. Institutional trust becomes particularly important during implementation when clarity, communication, and organisational capability shape professionals' interpretations of the process.

Sensemaking theory adds a third dimension by explaining how professionals interpret unexpected or ambiguous events, such as the interruption of an AI pilot. When direct experience with a technology is limited, individuals rely on organisational cues, contextual information, and communication to construct meaning. In this thesis, these interpretive responses are conceptualised as post-interruption perceptions. These perceptions are interpretive and sensemaking-based, focusing on organisational readiness, technological maturity, resource allocation, and institutional trust rather than on the performance of the AI system itself.

This framework supports a two-pathway understanding of perceptions. Evaluative attitudes represent pre-implementation perceptions shaped by acceptance determinants and technology level trust. Interpretive post-interruption perceptions emerge through sensemaking processes and focus on institutional trust and organisational behaviour. By distinguishing these two pathways, the thesis provides a coherent structure for analysing both baseline expectations and the interpretive responses triggered by an interrupted implementation.

Chapter 2 - Methodology

This study aims to examine health care professionals' perceptions of AI before and after the interruption of the pilot and to understand how the interruption is interpreted as impacting their trust, attitudes, and expectations toward the use of AI in health care. Guided by the theoretical framework, the study focuses on two research questions:

1. How did health care professionals perceive AI before the pilot?
2. How did the interruption of the AI pilot influence professionals' perceptions and trust?

This study employs an explanatory sequential mixed-methods design. The first research question was examined through a structured survey, and the second through semi-structured thematic interviews. This combination provides both breadth and depth: the survey yielded measurable patterns, while the interviews offered interpretive insight into the sense-making processes triggered by the interruption.

In line with the sequential design, quantitative results informed sampling for the qualitative phase. Survey participants with diverse perceptions were invited to participate in interviews. Interview themes were then used to explain and contextualise the quantitative patterns.

2.1 Survey Design

A structured survey instrument was developed to investigate health care professionals' attitudes toward AI, perceived competence regarding AI usage, and affinity for technology interaction. The data collected from the survey constituted the source for addressing the initial research question of this study. The survey comprised both single-item indicators and multi-item sets, the latter of which were designed to assess broader constructs.

The items were developed based on insights from previous literature, and they were not directly derived from any existing standardized instrument. The items surveying attitudes focused on capturing expectations regarding efficiency, usability, performance, and future use of AI in work. Each attitude item's link to former literature is presented in Table A.1.

AI was defined in the survey introduction as follows: *Artificial Intelligence is a term for technologies that enable machines and computer programs to perform tasks that normally require human intelligence. This includes, for example, reasoning, learning, and understanding speech. However, AI does not function like the human mind; instead, it solves tasks using programmed rules, given instructions, and models learned from large amounts of data.*

Demographic data were included to enable the analysis of group-level differences. While the survey instrument primarily consisted of closed-ended items, a single open-ended question was included to capture additional qualitative insights, enriching the interpretation of the findings.

The original survey was provided in Finnish, and the information was translated into English for reporting purposes. Translations aimed to preserve the semantic meaning of the items and the responses. The survey consisted of multiple sections, and the sections used in this study are summarised in Table 2.1. Attitudes and perceived AI competence were measured using four-point Likert-scale items without a neutral midpoint to reduce central-tendency bias and to encourage respondents to express a directional attitude.

Table 2.1 Overview of Survey Sections and Measurement Content

Survey section	Content	Measurement type	Purpose in Analysis
Demographics	Gender, age group, years of work experience, occupational group, organisation, work unit	Categorical	Describe sample characteristics and enable group-level comparisons
AI Usage	Frequency of AI use at work and during leisure time	Categorical options (never, tried a few times, occasionally, weekly, daily)	Examine associations between prior exposure to AI and attitudes/competence
Attitudes toward AI	19 items assessing usefulness, ease of use, performance expectations, trust, perceived risks, and intention to use	4-point Likert scale (strongly disagree - strongly agree)	Construct composite attitude score; analyse determinants of baseline perceptions
Perceived AI competence	9 items measuring knowledge, motivation, confidence, readiness, and perceived ability to evaluate AI output	4-point Likert scale (strongly disagree - strongly agree)	Construct a composite competence score; analyse its association with attitudes
Perceived Usefulness	Overall usefulness of AI in the respondent's own work	0–10 numerical rating scale	Assess general expectations about work-related usefulness
Open-ended question	Additional reflections on the use of AI in health care	Free-text response	Provide qualitative context to complement quantitative findings

Survey data were collected using the Webropol online survey platform. Separate versions of the survey were created for each wellbeing services county. Upon completion of data collection, the responses were merged for analysis. Participant recruitment was facilitated through the study contact persons within each county, who distributed email invitations to personnel in the relevant work units. These invitations included an overview of the study, a personalized survey link, a participant information sheet, and a privacy notice. All health care professionals working in the pilot units were invited to respond to the survey.

The survey launched in Hyvaks on 19.5.2025 and in Eloisa on 2.6.2025. The first reminder was sent on 10.6.2025, and the response deadline was extended until 11.8.2025.

2.2 Thematic Interviews

To explore participants' interpretations of the pilot interruption and its implications for trust and perceptions of AI, a semi-structured interview guide was designed. A thematic interview is suitable for studying people's experiences and the meanings people assign to matters. Interviews focus on specific themes, but not all aspects of the interview are predetermined. Thematic interviews do not require a specific shared experience but rather emphasize the interviewees' experiences and definitions of situations (Hirsjärvi & Hurme, 2014).

The interview structure was developed collaboratively with the research group and included open-ended questions and prompts to encourage participants to reflect on their expectations, concerns, and experiences. While themes provided structure, open-ended questions allowed flexibility for participants to elaborate on their experiences. The following themes were covered in the interviews of this study:

1. Perceived impact of the interruption on trust in pilot decision-makers and technology supplier
2. Perceptions of and responses to the interruption itself
3. Perceived impact of the interruption on views of AI usage in health care

Probing questions were used to clarify responses and encourage reflection on the ethical, practical, and organisational aspects of the interruption. The following sample questions were included:

- "How did the interruption affect your trust in the pilot decision-makers?"
- "How did you feel about the interruption?"
- "Did the interruption raise ethical questions?

Interviewees were recruited in person via email. The interviews were conducted remotely using Microsoft Teams, and they were recorded for further analysis. The interviews took place between 29 October and 18 November 2025 and lasted approximately 20-40 minutes each.

Chapter 3 - Data Analysis

This chapter outlines the analytical procedures applied to address the research questions. It is structured into two parts: the quantitative analysis of the survey data and the qualitative content analysis of the interview material.

3.1 Quantitative Analysis of Survey Data

The quantitative analyses were conducted using IBM SPSS Statistics (version 31.0.0.0). Before the analyses, the survey dataset was screened for completeness. Two cases with extensive missing values were removed, resulting in a final sample of 75 respondents. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were calculated to summarise the sample and to inform subsequent inferential analyses. Age, work experience, and AI-use variables were recoded into broader categories to ensure adequate group sizes and to meet the assumptions of parametric tests. For AI usage, the response categories were further collapsed into two groups, distinguishing between respondents who had never used or had only tested AI and those who reported at least occasional use. This recoding supported the group comparisons conducted in the results.

Composite scores were created for Attitudes toward AI and Perceived AI Competence by computing the mean of the relevant Likert-scale items. Two attitude items were negatively worded and were reverse-coded before calculation. Internal consistency was assessed using Cronbach's alpha, and item-total correlations were examined to ensure that each item contributed meaningfully to its respective construct. Composite score construction was consistent with the analytical strategy outlined in the theoretical framework.

Assumptions for the planned analyses were examined using the Shapiro-Wilk test for normality, Q-Q plots, and Levene’s test for homogeneity of variance. Group differences in attitude scores were tested using independent-samples t-tests or Welch’s t-tests when variances were unequal. A one-way ANOVA was used to examine differences across work-experience categories. Effect sizes were reported using Cohen’s d for t-tests and eta-squared for ANOVA.

Associations between attitudes and perceived AI competence were examined using Spearman’s rank-order correlation. Although the attitude score was approximately normally distributed, the competence score showed slight deviation from normality. Visual inspection of the scatterplot indicated a monotonic but not strictly linear relationship between the variables, which supported the decision to use a non-parametric correlation method.

The responses of the open-ended question were summarised using qualitative content analysis to provide contextual insight that complemented the quantitative findings. Visualisations were produced to support the interpretation of the results.

3.2 Qualitative Analysis of Interview Data

The interview data were analysed using qualitative content analysis. A theory-driven content analysis was applied, in which observations are not derived directly from theory; instead, theory functions as a supportive framework guiding the analytical process. In theory-driven analysis, the units of analysis are identified inductively from the data, while existing theoretical knowledge provides analytical support (Tuomi & Sarajärvi, 2018). Theory-driven content analysis is based on abductive reasoning, whereby theory development becomes possible when observations are guided by a sensitising theoretical framework (Alasuutari, 2011).

The collection and analysis of qualitative data, as well as the development of the theoretical framework, were conducted iteratively throughout the research process. The analysis of qualitative data was linked to the analysis of quantitative data and informed the reorientation of the research process as the study progressed. The themes of the thematic interviews guided the identification and definition of the units of analysis.

The analysis proceeded in three stages: reduction, clustering, and abstraction (Miles & Huberman, 1994, as cited in Tuomi & Sarajärvi, 2018). The analytical process began with the transcription of the data. All interviews were transcribed verbatim from video recordings into text form as accurately as possible to preserve their original meaning. The automatic transcription feature provided by Microsoft Teams was used as an initial step. The transcripts were subsequently reviewed by listening to the recordings multiple times, and necessary corrections were made manually utilizing Microsoft Word.

After transcription, the interview transcripts were read several times to gain an overall understanding of the content and to make preliminary observations related to the research phenomenon. The data were then reduced by coding verbatim participant quotes addressing similar aspects of the phenomenon. Coding was conducted manually using the QualCoder (version 3.7) software. The coded participant quotes were exported into a separate table-formatted text file and further analysed in Microsoft Word by condensing the quotes into condensed meaning units, which were subsequently grouped into categories.

The interviews were conducted in Finnish, and the qualitative data were managed in the original language. For reporting purposes, expressions were translated into English, aiming to preserve the original semantic meaning. Through the processes of categorisation and abstraction of meaning content, the data were gradually organised into broader conceptual entities (Elo et al., 2022). Interview quotes are coded as P# to indicate anonymised interviewees (e.g., ‘P1’).

Three integrative main categories were identified. The main categories and an example of the abstraction process are presented in Table 3.1. A total of 9 categories and 26 subcategories were constructed. Although subcategory counts (n) are presented in the qualitative results tables, they serve

only to illustrate the distribution of meaning units within this sample and should not be interpreted as quantitative measures of frequency.

Table 3.1 Example of the Interview Data Abstraction Process

Participant quote	Condensed meaning unit	Subcategory	Category	Main category
"…I want more information about this, what led to it, whether it was due to cost-cutting measures or whether there was some structural flaw in the program itself, or what led to this, so that I can form my own opinion." (P3)	Trust can be assessed once more information has been obtained	Conditional trust	Trust in the AI pilot decision-makers	The impact of interruption on trust
"…then I wondered how it would be applicable for patient guidance at all." (P1)	I doubt that AI is suitable for patient guidance	Doubts about the suitability of the technology	Issues related to reliability, suitability, and data quality	Interruption and Views on the Use of AI in Health Care
"Well, yes, it [the interruption] was a bit disappointing." (P1)	The interruption caused disappointment.	Disappointment	Responses to the Interruption	Perceptions of interruption

Chapter 4 - Data Protection and Management

The study followed strict data protection and ethical standards throughout the data collection, processing, and storage phases. A research permit was obtained from both pilot organisations before data collection. Personal data were collected through both a structured online survey and semi-structured thematic interviews. All data handling complied with the European Union's General Data Protection Regulation (GDPR, 2016), the Finnish National Data Protection Act (2018), and the data protection guidelines of the participating wellbeing services counties.

The processing of personal data was based on informed consent. Participants received a participant information sheet and a privacy notice before participating, which explained the purpose of the study, the nature of the data collected, the rights of the participants, and the procedures for data protection. Participation was voluntary, and all respondents were of legal age.

The survey collected personal identifiers such as email address, job title, organisation, and work unit, as well as demographic information including age group and work experience. The interviews were recorded using video and audio, with consent from the participants. No sensitive personal data, such as medical records, was collected. The data were used exclusively for scientific research purposes.

To ensure confidentiality, all identifying personal data were pseudonymized at the data creation stage. A key code register was created to enable participant-level analysis while protecting identities. This register was stored securely and was accessible only to the research director and the data controller. Pseudonymized data were used for all analysis and reporting, and the results are presented in a way that prevents identification of individual participants.

The research data were stored securely on platforms approved by Wellbeing Services County of Central Finland (Hyvaks). Survey data were collected via Webropol and stored on secure workstations and network disks accessible only to authorized personnel. Interview data were recorded via Microsoft Teams and stored on SharePoint/OneDrive in designated research folders. Access to all research files was restricted to members of the research group and granted only through personal credentials. Any external data processors, such as research assistants, were granted access only to pseudonymized data, and a data processing agreement was signed with the data controller to ensure compliance.

The pseudonymized survey data will be retained for two years following the conclusion of the research, in accordance with the guidelines of Hyvaks. The final disposal date is 31.12.2028. All data will be securely destroyed following the county's official procedures for research data disposal.

A data protection statement and a self-assessment of data protection risks were prepared for the study and were provided as annexes to the research plan. The implementation of the study was planned collaboratively with the research group, and Hyvaks acted as the data controller of the register. The research material collected during the study was entered into the research register by

the person responsible for the research. No other data controllers were authorized to enter data into the register. The research data were stored on the Arkki platform maintained by Hyvaks, which is accessible only to a limited number of authorized individuals. Access and viewing rights to the platform must be requested from the research experts of the county's research activities, and access requires personal identification. These measures ensured that the data were handled securely and in accordance with applicable data protection regulations and ethical standards.

The thesis process adhered to the principles of good scientific practice, including reliability, integrity, respect, and accountability (ALLEA, 2023; Keiski et al., 2023). All written work complies with the institution's guidelines for thesis preparation and ethical research conduct.

Chapter 5 - Results

This chapter presents the study results, reporting survey findings on attitudes toward AI and interview findings on interpretations of the pilot interruption.

5.1 Survey Results

This chapter presents the quantitative findings of the pre-pilot survey. The results are organized to provide a logical progression from sample characteristics to item set validation, descriptive patterns, group comparisons, and associations between perceived AI competence and attitudes.

The pre-pilot survey yielded a response rate of 44.1% based on 75 valid responses. The analyses focused on differences between age groups, work experience, AI training participation, and AI usage frequency. Composite scores were compared across these groups to identify patterns and significant associations.

5.1.1 Sample Characteristics

A detailed breakdown of respondent characteristics presented in Table 5.1 shows that the survey respondents were predominantly female (94.7%), and similarly, the majority (94.7%) reported their professional role as either nurse or public health nurse. The most represented age groups were 31–40 years (33.3%) and 41–50 years (29.3%), and nearly one-third (32.0%) of participants reported having over 20 years of work experience in the social and health care sector. The respondents were evenly distributed between two organisations: Eloisa with 50.7% and Hyvaks with 49.3%.

The data revealed a notable difference between work and leisure contexts on AI usage. At work, one-third of respondents (33.3%) reported never using AI applications, while 42.6% had only experimented with them a few times or used them infrequently. Regular use of AI at work remained limited, with only 14.7% using such applications weekly and 8.0% daily. In contrast, AI usage during leisure time was more prevalent: 42.7% of respondents reported using AI applications at least weekly, whereas only 13% indicated they had never used AI in their leisure time.

Table 5.1 Characteristics of the Survey Respondents

Characteristic	Category	n	%
Gender	Female	71	94.7%
	Male	4	5.3%
Age	20–30 years	10	13.3%
	31–40 years	25	33.3%
	41–50 years	22	29.3%
	51–60 years	14	18.7%
	Over 60 years	4	5.3%
Work Experience	0–5 years	7	9.3%
	6–10 years	17	22.7%
	11–15 years	19	25.3%
	16–20 years	8	10.7%
	Over 20 years	24	32.0%
Professional Role	Nurse / Public Health Nurse	72	94.7%
	Doctor	2	2.7%
	Physiotherapist	1	1.3%
Organisation	South Savo Wellbeing Services County	38	50.7%
	Wellbeing Services County of Central Finland	37	49.3%
Frequency of AI Usage at Work	Never	25	33.3%
	Tried a few times	16	21.3%
	Occasionally, rarely	16	21.3%
	Actively, weekly	11	14.7%
	Actively, daily	6	8.0%
	Missing	**1**	**1.3%**
Frequency of AI Usage in Leisure Time	Never	13	17.3%
	Tried a few times	12	16.0%
	Occasionally, rarely	17	22.7%
	Actively, weekly	24	32.0%
	Actively, daily	8	10.7%
	Missing	**1**	**1.3%**
Previously participated in AI-related training	Yes	28	37.3%
	No	47	62.7%

Note. N = 75.

Respondents rated the usefulness of AI in their own work on a scale from 0 (“not at all useful”) to 10 (“extremely useful”). The mean rating was 7.21 (SD = 1.73), indicating generally positive expectations. The distribution of responses is visualized in Figure 5.1.

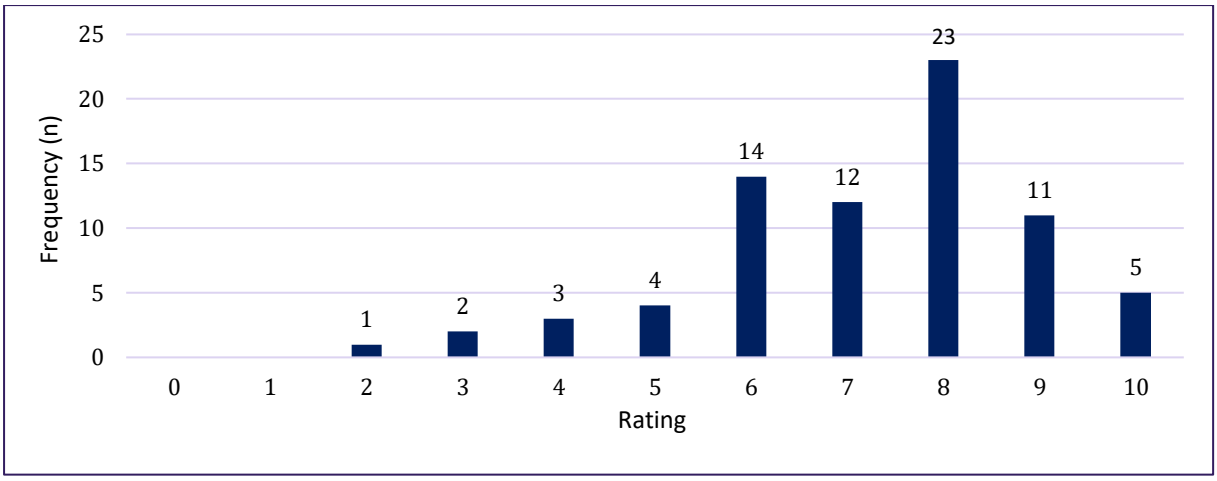


Figure 5.1 Distribution of Ratings for the Usefulness of AI in Respondents' Own Work

Note. N = 75. Source: Author's analysis.

5.1.2 Measurement Properties of the Attitude Items

Before computing the composite attitude score, the internal consistency of 19 items surveying attitudes was evaluated using all 75 valid responses. Examination of the item-total statistics showed that most items correlated adequately with the overall item set, indicating that they measured the same underlying construct. The last item of the set, "In the future, artificial intelligence may completely replace human labour", showed a very low corrected item-total correlation (CITC = 0.083) compared to the other items, which ranged from 0.27 to 0.75. In addition to this weak statistical performance, the item was also conceptually more controversial and extreme in content compared to the other items, which likely contributed to its poor coherence with the item set. Removing the item slightly improved internal consistency (Cronbach's α = 0.894), supporting the decision to exclude it.

The composite attitude score for subsequent analyses was therefore computed based on the remaining 18 items. Item-level descriptive statistics are provided in Table A.1.

5.1.3 Background Factors and Attitudes

Independent‐samples t‐tests were conducted to examine whether attitude scores differed between age groups. Participants aged 40 years or under reported more positive attitudes (M = 3.05) than participants over 40 years (M = 2.83). The difference between groups was statistically significant, t(73) = 2.29, p = .025 (two‐tailed), with a mean difference of 0.22 (95% CI [0.03, 0.41]). The effect size was moderate (Cohen's d = 0.53). Group means for the age groups are displayed in Table 5.2. These results suggest that younger professionals tend to hold more favourable views toward AI.

Table 5.2 Attitude Scores by Age Group

Age Group	n (%)	Mean	SD
40 years or under	35 (47%)	3.05	0.41
Over 40 years	40 (53%)	2.83	0.42

Note. N = 75.

A one-way ANOVA was used to compare attitude scores across three work experience groups. The test was not statistically significant, $F(2, 72) = 2.75$, $p = .071$, with an effect size of $\eta^2 = .071$ (95% CI [0.00, 0.19]). Descriptively, attitude scores were highest among those with under 10 years of experience, followed by 10–20 years and over 20 years. Tukey's HSD post hoc tests did not reach statistical significance and therefore are not reported. Although the differences were not statistically significant, the descriptive pattern in Table 5.3 indicates that less experienced professionals may perceive AI somewhat more positively.

Table 5.3 Attitude Scores by Work Experience

Work Experience	n (%)	Mean	SD
Under 10 years	24 (32%)	3.09	0.46
10-20 years	27 (36%)	2.91	0.29
Over 20 years	24 (32%)	2.81	0.48

Note. N = 75.

An independent-samples t-test was conducted to examine whether participation in AI-related training was associated with differences in attitude scores. Participants who had attended AI training reported slightly higher attitude scores (M = 3.02) compared with those who had not attended such training (M = 2.89). Levene's test indicated homogeneity of variance between the groups ($F = 0.25$, $p = .617$). The differences were not statistically significant, $t(73) = 1.28$, $p = .204$ (two-tailed), and the 95% confidence interval for the mean difference [-0.07, 0.33] included zero. The corresponding effect size was small (Cohen's $d = 0.31$). These results suggest that training did not substantially influence attitudes. Composite attitude scores by training participation are summarised in Table 5.4.

Table 5.4 Attitude Scores by AI Training Participation

Training participation	n (%)	Mean	SD
Yes (attended)	28 (37%)	3.02	0.38
No (not attended)	47 (63%)	2.89	0.45

Note. N = 75.

Independent-samples t-tests were conducted to examine whether use of AI, either in leisure time or at work, was associated with differences in attitude scores. One pairwise missing value resulted in N = 74 for the analyses.

Participants who had never used or only tested AI in their free time reported lower attitude scores (M = 2.71) compared with those who used AI at least occasionally (M = 3.06). The difference between the groups was statistically significant, t(72) = -3.57, p < .001 (two-tailed), with a mean difference of -0.35 (95% CI [-0.54, -0.15]). The effect size was large (Cohen's d = 0.88).

Participants who had never used or only tested AI at work reported lower attitude scores (M = 2.82) than those who used AI at least occasionally at work (M = 3.09). This difference was statistically significant, t(72) = -2.94, p = .004 (two-tailed), with a mean difference of -0.28 (95% CI [-0.47, -0.09]). The effect size was medium-to-large (Cohen's d = 0.69).

As illustrated in Table 5.5, these findings suggest that even infrequent professional AI usage appears to be associated with more favourable attitudes toward AI. The relationship mirrors the pattern observed for leisure-time use.

Table 5.5 Attitude Scores by AI Usage

Usage context	Group	n (%)	Mean	SD
Leisure	Never / tested only	25 (33%)	2.71	0.35
	Uses at least occasionally	49 (65%)	3.06	0.41
At-work	Never / tested only	41 (55%)	2.82	0.40
	Uses at least occasionally	33 (44%)	3.09	0.40

Note. N = 74.

5.1.4 Perceived AI Competence and Attitude

Reliability of the nine survey items (presented in Table A.2) surveying Perceived AI Competence was confirmed, resulting in a Cronbach's alpha value of 0.888 referring to a reliable analysis. Corrected item-total correlations ranged from .49 to .81, indicating that all items contributed meaningfully to the construct. A composite competence score was computed for further analysis.

Before examining the association between competence and attitude scores, normality and functional form were assessed. Shapiro-Wilk tests showed that the attitude score was approximately normally distributed (W = .982, p = .352), whereas the competence score showed slight deviation from normality (W = .967, p = .048). Visual inspection of scatterplots further indicated that the association between the variables was monotonic but not strictly linear. Given the slight non-normality and the non-linear pattern observed, Spearman's rank-order correlation was used to assess the association between competence and attitude scores. The correlation between perceived AI competence and attitudes toward AI is presented in Figure 5.2.

The results indicate a strong, positive, and statistically significant association (ρ = 0.619, p < .001, N = 75), indicating that higher perceived competence was associated with more favorable attitudes toward AI.

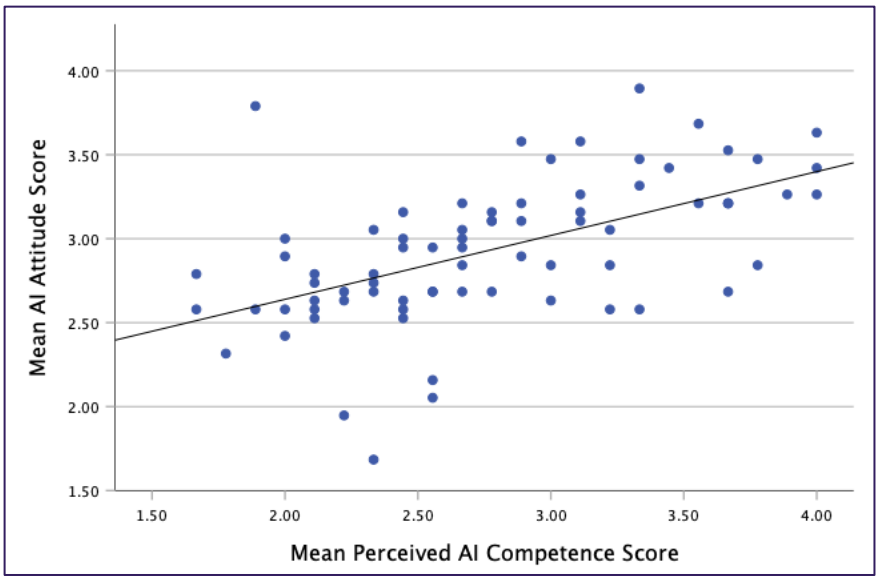


Figure 5.2 Association Between Perceived AI Competence and Attitudes Toward AI

Note. Source: Author's analysis

5.1.5 Professionals' Pre-Interruption Reflections on AI Usage

A total of sixteen participants responded to the open-ended question asking what else they would like to say about the use of AI.

Several participants highlighted the importance of adequate orientation and peer support when AI-assisted tools are introduced. One participant noted, *"When it becomes available, I hope there is enough time for orientation and support from colleagues."* Others emphasized that without sufficient training, it is difficult to assess the relevance of AI in health care, stating, *"I have not received any training, so I cannot say anything about its benefits or drawbacks."*

Attitudes toward AI as a tool were generally favorable yet tempered by a request for human oversight. For example, one participant wrote, *"Welcome AI, but only as a tool - its outputs must always be critically reviewed."* Another participant stressed the importance of source criticism, suggesting that *"users should not take AI outputs as absolute truth."*

Some responses reflected enthusiasm about the upcoming pilot and its potential to improve client work and service delivery. Others offered concrete suggestions for utilizing AI, such as guiding clients to appropriate services or assisting with documentation and scheduling.

The responses indicate that professionals perceived AI as a promising but complex addition to health care work. Their views were shaped by expectations of usefulness, concerns about autonomy

and workload, and the need for sufficient support and training. Many participants expressed cautious optimism toward AI, recognizing its potential to support professional tasks while also emphasizing the need for critical evaluation and proper training.

5.1.6 Variation Across Individual Attitude Items

While overall attitudes toward AI were generally positive, individual items were also examined to complement the analysis and to provide a more nuanced understanding of participants' views. The item-level analysis highlights specific items with strong consensus and divided opinions. The Likert-scale responses were combined into two categories for reporting purposes.

Figure 5.3 highlights the overall leanings of the items by contrasting disagreement with agreement around a central zero point.

A strong majority agreed that AI offers clear benefits, such as improving continuity of care and reducing waiting times (86.6%). High levels of agreement were observed regarding AI's potential to enhance consistency in care assessments (92.0%), improve work efficiency (89.3%), and support future work practices (94.6%). There was strong consensus (94.6%) against the idea that AI could fully replace human labour in the future.

The respondents were split on whether AI users are more efficient than non-users (agree: 54.6%, disagree: 45.4%) and whether AI is effortless to use (agree: 49.3%, disagree: 50.7%). Trust in AI-generated recommendations also emerged as a point of disagreement, with 48.0% agreeing and 52.0% disagreeing that such recommendations are as reliable as those made by humans.

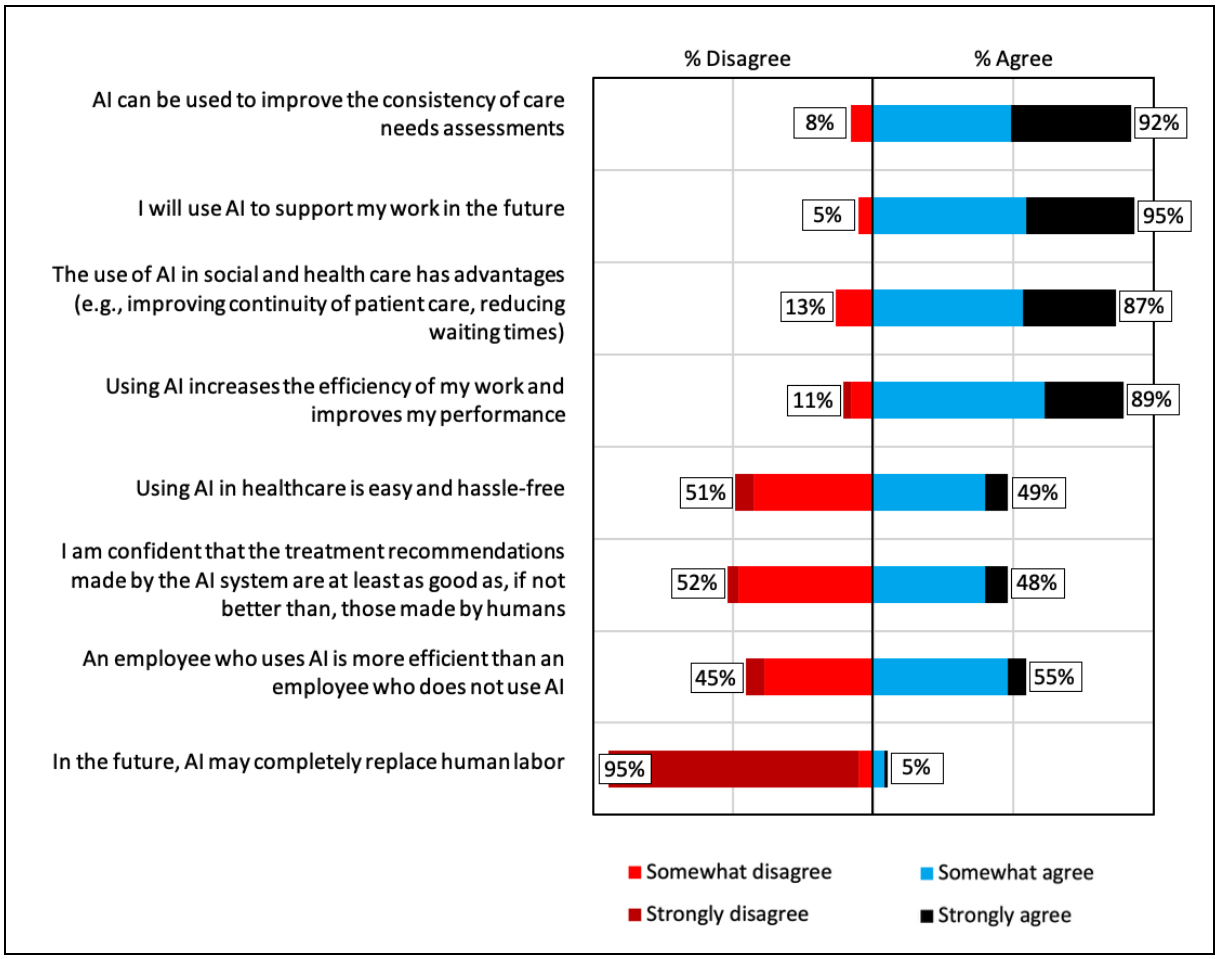


Figure 5.3 Attitudinal Leanings for Selected Attitude Items

Note. Proportion is calculated on N = 75. The second item in the figure was missing one value. All four Likert response categories (1–4) are shown, but the percentage labels represent only the combined disagreement (1–2) and agreement (3–4) groups. The central zero line separates these combined groups and is not the midpoint of the scale. Source: Author's analysis.

5.2 Interview Findings

This chapter presents the qualitative findings from semi-structured interviews conducted after the pilot was interrupted. The analysis focuses on how participants interpreted the interruption and how it influenced their trust and perceptions of AI in health care. Findings are organized into three themes: perceived impact of the interruption on trust, perceptions of the interruption, and interruption and views on the use of AI in health care. The participants' sensemaking of the interruption within their organisational context is emphasized rather than revising their technology-level attitudes.

A total of 22 survey respondents were invited, of whom six participated. Despite a sampling strategy aimed at capturing diverse perspectives, the final interviewees represented low-to-middle attitude and competence scores in the survey phase. Half (n = 3) had under 10 years of experience; the other half had 10–20 years. Two interviewees were over 40 years of age. In the initial survey, the

interviewees' assessments of the usefulness of AI in their own work ranged from 3 to 8 (M = 5.67, SD = 1.86). All the interviewees also reported that they did not know the reasons for the pilot's interruption.

5.2.1 Perceived Impact of the Interruption on Trust

Participants described how the pilot's interruption affected their trust in the AI pilot's decision-makers and the technology provider. Table 5.6 summarises the subcategories identified.

Table 5.6 Trust-related Interpretations of the Interruption

Category	**Subcategory**
Trust in the AI pilot decision-makers	Stable trust (n = 6)
	Conditional trust (n = 1)
Trust in the AI technology provider	Stable trust (n = 2)
	Conditional trust (n = 1)
	Distrust (n = 2)

Note. Subcategory counts (n) illustrate the distribution of meaning units within the sample

A recurring view was that the interruption of the AI pilot had no impact on trust in the pilot's decision-makers. A stable and unchanging trust towards both superiors and higher-level decision-makers was consistently highlighted. One interviewee described their trust by saying that the project had not affected their views in any way, nor had it changed their attitude towards the pilot's initiators or the wellbeing county more broadly.

The data highlighted the view that temporary trials play a role in organisational development and that this was not perceived to have an impact on trust in decision-makers. One interviewee also perceived the AI pilot as a relatively small part of other changes in the welfare county and, from this perspective, did not see it as affecting trust.

> *"Experiments come and go, and you have to try them out to see what works and what doesn't"* (P6)

However, one interviewee stood out in the material by stating that their trust was conditional on receiving additional information about the background and grounds for the decision, saying, "*I want more information about the matter, i.e., what led to it... then I can form my opinion*" (P3).

Some of the interviewees felt that the interruption of the AI pilot had no impact on their trust in the technology provider. These responses reflected a stable and unchanging level of trust, which was

described with straightforward statements such as *"I don't think so-at least not in my case"* (P4) and *"No, I can't say that it had any impact"* (P6).

Based on the data, shifts in trust were described in connection with the interruption. Doubts arose about the level of technological development and the maturity of the technology. The readiness of the technology was doubted in a situation where it is already offered to the organisation.

In addition, mistrust was expressed regarding the values and operating principles of the technology supplier. According to one interviewee, trust in the technology supplier had probably not changed, but the assessment remained open due to a lack of information about the reasons for the interruption. Critical questions were raised as to whether technological development is primarily driven by economic interests at the expense of health care and broader social responsibility.

> *"Do these technology suppliers prioritize health care at all, or is it just a case of money coming first in developing these products, while social responsibility is somehow forgotten?"* (P1)

5.2.2 Perceptions of the Interruption

Participants' responses to the interruption ranged from neutral/positive acceptance to disappointment and included a desire for an alternative solution. Grounds for acceptance were pragmatic: data quality, limited need, timing, and financial considerations, as presented in Table 5.7 below.

Table 5.7 Professionals' Perceptions and Reactions to the Interruption

Category	**Subcategory**
Responses to the Interruption	Neutral or positive attitude (n = 4)
	Disappointment (n = 5)
	Desire for an alternative solution (n = 2)
Grounds for Accepting an Interruption	Concerns about data quality (n = 1)
	Lack of need for the AI-assisted tool (n = 1)
	Timing of the pilot (n = 1)
	Financial considerations (n = 2)
Perceived Benefits of the Interruption	Future use of the gained knowledge (n = 1)
	Benefits of financial investments in the future (n = 1)

Note. Subcategory counts (n) illustrate the distribution of meaning units within the sample

Several interviewees viewed the interruption neutrally or positively, although disappointment was also common. In addition, the idea was raised that continuing the pilot at this stage could have been questionable in terms of resources. The data repeatedly described the disappointment caused by the

interruption. One interviewee described feeling disappointed but still had a positive attitude toward the interruption.

One interviewee expressed the desire and need to find an alternative solution to replace the interrupted pilot, stating, *"I hope that something else will replace it"* (P3).

The acceptability of the interruption was justified on several pragmatic grounds. First, the key reason given was the experience that the AI-tool used in the testing phase did not meet user needs or offer sufficient benefits. The timing of the pilot was considered unfavorable, and interruption was deemed acceptable at this point, also in terms of resources.

> *"…as I was in the test group and saw the answers it gave, I thought that [discontinuing it] was a good thing. That I wouldn't have found it helpful in any way."* (P2)
> *"Maybe it just wasn't the right moment. In that case, it's better not to push it any further, but to wait for the right moment to come later."* (P6).

In addition, financial considerations influenced the understanding of the interruption. One interviewee did not see investing in the project as particularly appropriate in the current economic situation.

> *"Is it sensible in this situation to pour so much of our limited funds into RDI activities, or would it be better to focus on something else […]? I am relatively satisfied that no more money was spent on that project this time around."* (P5).

Although the interruption was considered unfortunate in some cases, some of the interviewees emphasized that the pilot project was not entirely useless. The information gathered during the pilot, such as preliminary groundwork on the tool, was considered useful for future development phases. One participant stated that although money had been spent, it had not been "*completely wasted*" because the work done in the pilot *"provides a starting point from which to continue"* (P6).

5.2.3 Interruption and Views on the Use of AI in Health Care

Interviewees generally reported that the interruption did not substantially change their underlying views of AI as a technology. Instead, it drew attention to a few ethical concerns, data protection, and reliability and suitability issues as presented in Table 5.8.

Table 5.8 Professionals' Views on the Use of AI Following the Interruption

Category	**Subcategory**
Ethical issues	Few ethical concerns (n = 1)
	Patient safety (n = 1)
	Ethics of financial investments (n = 1)
Data protection	Concerns about data protection (n = 1)
	Training and data protection expertise (n = 1)
	Confidence in the implementation of data protection (n = 1)
Issues related to reliability, suitability, and data quality	Uncertainty about reliability (n = 5)
	Doubts about the suitability of the technology (n = 2)
	Doubts about the sufficient development of AI (n = 2)
Impact on attitudes	Stable attitude (n = 8)
	Evaluation requires more user experience (n = 1)

Note. Subcategory counts (n) illustrate the distribution of meaning units within the sample

Interviewees did not raise many ethical questions about the use of AI after the interruption. Data revealed the view that patient safety is a fundamental guideline in health care, within the framework of which new technology is evaluated. One respondent stated that the interruption *"did not really raise any major ethical concerns,"* while emphasizing that *"patient safety is at the heart of everything"* (P4).

The interview data raised broader ethical considerations regarding the use of public funds and the sustainability of investments. One interviewee expressed concern that investments in technology projects could become ethically problematic if there is insufficient financial accountability and critical evaluation. This concern crystallized into the idea that ethics should guide decision-making, especially when it comes to the use of tax revenues. Thus, ethical considerations focused more on the justification and responsibility of investments than on the use of AI technology in health care itself.

> *"Well, to put it bluntly, 'there's free money up for grabs,' so in a way, it would be like, let's not milk this cash cow dry"* (P5).

Some practical considerations were brought up related to data protection. Some of the interviewees considered the use of AI in health care from the perspective of whether essential or sensitive information that could pose a security risk could inadvertently end up in the system.

> *"…I also considered the security aspect. Could really important information be sent there that could pose a security risk?"* (P1)

One respondent stated that they did not consider data protection issues to be relevant, as AI was not used in the processing of patient data. In addition, the importance of user training in ensuring security was highlighted. According to one interviewee, inadequate training could lead to situations where critical or personally identifiable information is entered into the system.

A typical finding was that uncertainty was expressed about the quality and reliability of the information produced by AI. Uncertainty was described, for example, in terms of the information provided by AI not meeting expectations.

> *"…you shouldn't blindly trust the information provided by the tool."* (P5)
> *"I felt a little uncertain about the quality of what it produced."* (P2)

The suitability of AI technology for patient guidance tasks was also questioned. One interviewee described how the general discussion about AI gives a different impression of its usability than is actually the case.

> *"I myself think that the hype surrounding artificial intelligence is a bit overblown, that people have really high expectations of it, and perhaps it isn't as versatile as people think it is"* (P1)

In addition, it was estimated that the system used in the pilot might have been brought to the testing phase at too early a stage of development. The material raised doubts as to whether AI is yet sufficiently advanced to be utilized in the interviewee's own health care unit.

A typical feature of the data was that respondents reported that their attitudes toward the use of AI remained unchanged despite the interruption. Several participants explicitly stated that their attitudes had not changed in any direction. A cautious attitude toward the technology also emerged in the data. One respondent stated that they were unable to assess the effects due to their limited experience with the technology.

> *"No, it hasn't swayed [views in any direction]. Not one way or the other."* (P5)
> *"I have this kind of realistic caution or attitude [...] related to using my own common sense and intelligence."* (P6)

Chapter 6 - Discussion

This study suggests that health care professionals' perceptions of AI evolve along interconnected but distinct pathways. These pathways include evaluative attitudes formed before implementation and interpretive perceptions shaped by organisational events during implementation. This conclusion aligns with the theoretical framework, which integrates technology acceptance models, trust research, and sensemaking theory. Acceptance determinants shape early expectations, technology level trust forms part of these expectations, and institutional trust becomes central when implementation processes shift in unexpected ways.

The quantitative findings describe baseline expectations before the interruption of the pilot. Attitudes toward AI were generally positive and reflected expectations that AI could improve efficiency, continuity of care, and the consistency of assessments. These results are consistent with previous studies that show how professionals recognise the potential of AI to support documentation, reduce workload, and strengthen clinical reasoning (Henzler et al., 2025; Lambert et al., 2023; Topol, 2019). At the same time, respondents expressed reservations about reliability, transparency, and the relationship between AI recommendations and professional judgement, which aligns with findings of conditional optimism and concerns related to technological maturity, uncertainty, and safety (Ayorinde et al., 2024; Chew & Achananuparp, 2022). Several of the attitude items in this study also reflected trust-related evaluations, indicating that pre-implementation attitudes include expectations related to reliability, risk, and credibility. These elements reflect technology-level trust, which appears embedded in the evaluative attitudes captured in the survey.

Differences between respondent groups were consistent with established dynamics in technology acceptance research. Younger professionals and those with less work experience reported more favourable attitudes, a pattern that reflects research showing that digital familiarity and openness to technological innovation shape expectations (Choi 2023; El Arab et al., 2025; Henzler et al., 2025). Both at work and in leisure time, more frequent AI use was associated with more positive attitudes, suggesting that prior exposure and perceived competence support favourable evaluations. The strong association between perceived competence and attitudes reinforces this interpretation. Participation in AI-related training did not show a significant association with attitudes, which is consistent with research suggesting that generalised training is less effective than training embedded in actual workflows or supported by hands-on interaction (Hassan et al., 2024; Wang et al., 2023). These quantitative findings indicate that pre-implementation perceptions are shaped by experience-based confidence, expectations of usefulness and ease of use, and competence-related beliefs.

While the quantitative results describe early evaluative perceptions and technology-level trust, the qualitative analysis illustrates how professionals interpreted the interruption of the pilot. Because

participants had limited or no hands-on experience with the AI assistant, they lacked direct evidence regarding the system's usefulness, reliability, or ease of use. Sensemaking theory suggests that under such conditions, individuals rely on contextual cues and organisational communication when trying to understand unexpected events (Weick, 1995; Weick et al., 2005). The interview findings reflect this process. Participants interpreted the interruption through organisational signals such as communication quality, timing, perceived readiness, and assumptions about technological maturity (Brown et al., 2014; Petersson et al., 2022). Their responses focused on whether the interruption reflected responsible decision-making, insufficient organisational readiness, shifting priorities, or limitations of the technology itself.

Attitudes toward AI as a concept remained largely unchanged. This stability is consistent with the understanding that attitudes form early and tend to remain unchanged without direct experience that would confirm or challenge them. Interpretive perceptions related to the interruption, however, were more dynamic. Interviewees evaluated the organisation's capacity, governance, and clarity, which aligns with research showing that institutional trust depends on transparency, communication, and perceived competence (Steerling et al., 2023; Wang et al., 2023). Some participants associated the interruption with questions about organisational priorities or the responsible use of public resources. Others viewed the decision as reasonable considering limited benefits, technological immaturity, or financial pressures. These interpretations show that the interruption functioned primarily as a cue for evaluating institutional trust rather than technology-level expectations.

Ethical considerations identified in the interviews centred on organisational responsibility, patient safety, and the appropriate use of public funds. This pattern aligns with earlier literature suggesting that ethical evaluations in AI projects often concern organisational decision processes rather than technical issues alone (Petersson et al., 2022). Respondents also expressed uncertainty regarding the reliability and suitability of the system, reflecting broader patterns in early-stage AI adoption in which expectations are shaped by limited experience and concerns about data quality, accuracy, and readiness (Niemelä et al., 2025; Sun & Medaglia, 2019). Because the interview participants represented more cautious or uncertain attitudes in the survey sample, their interpretations may have also emphasized organisational uncertainty, technological immaturity, and conditional trust.

The findings suggest that interrupted implementations are interpreted in ways that differ from typical adoption scenarios. Baseline attitudes appear to remain grounded in acceptance determinants and technology-level expectations. Post-interruption perceptions, however, are shaped through sensemaking processes that centre on organisational readiness, communication quality, and institutional credibility. This suggests that AI adoption involves both technological and organisational processes, and that organisational signals take precedence when hands-on experience is absent. The findings also illustrate the relevance of sensemaking when implementation does not progress as

anticipated, since interpretations depend on cues in the organisational environment rather than on system performance (Weick, 1995; Weick et al., 2005).

These findings have several implications for planning future AI initiatives in health care organisations. Interruptions and unexpected changes require clear and timely communication to support institutional trust. Opportunities for early engagement and trial use can help professionals form evaluations based on experience rather than speculation. Strong governance structures, alignment with regulatory requirements such as the GDPR and the AI Act, and realistic assessments of technological maturity can support perceptions of readiness. Implementation planning should also consider timing, workload, resources, and links to broader strategic goals. Communicating both the possibilities and limitations of AI is essential for fostering realistic expectations and supporting sustainable adoption.

Conclusion

This study explored how health care professionals' perceptions of artificial intelligence develop in the context of an interrupted implementation. The findings suggest that perceptions follow two interconnected pathways: evaluative attitudes formed prior to implementation and interpretive perceptions shaped by organisational events. While baseline attitudes toward AI were generally positive and grounded in expectations of usefulness and efficiency, the interruption was primarily associated with reflections on organisational readiness, communication, and institutional credibility.

The results indicate that the interruption was more closely linked to reconsiderations of institutional trust than to changes in underlying attitudes toward AI itself. In the absence of direct system experience, professionals relied on organisational cues to interpret the meaning of the interruption. Through sensemaking processes, attention shifted from technological expectations to evaluations of governance, transparency, and strategic preparedness.

These findings contribute to AI adoption research by highlighting the importance of implementation trajectories, particularly when projects do not unfold as planned. Adoption does not appear to be solely a linear progression toward use; interruptions may function as interpretive turning points in which trust in the organisation becomes central.

Practically, the study underscores the value of transparent communication, realistic expectation management, and visible organisational preparedness when introducing AI in health care. Trust in AI is closely intertwined with trust in the institutions responsible for its deployment.

Future research should examine how institutional trust develops after interruptions, how perceptions shift as organisations provide new information, and how different implementation trajectories influence expectations and readiness. Longitudinal and comparative studies, as well as research involving a wider range of professional groups, would offer deeper insight into how organisations can support responsible and sustainable use of AI.

Limitations

This study has several limitations that should be considered when interpreting the findings. The qualitative sample was small and reflected respondents with lower levels of attitudes and perceived competence in the survey. Although this provided insight into the views of more cautious professionals, it narrowed the range of perspectives and may have excluded those who hold more enthusiastic or technologically confident views. The survey relied on self-reported data, which may be affected by social desirability, recall bias, or varying interpretations of artificial intelligence.

The sample size of 75 survey respondents was adequate for descriptive purposes but limited the statistical power to detect subgroup differences. The strong predominance of nurses and public health nurses also restricts generalisability, since physicians and other professional groups were minimally represented. As a result, the findings mainly reflect perceptions characteristic of nursing-oriented work environments. As participation was voluntary, it is possible that respondents with greater interest, experience, or confidence in AI were more likely to complete the survey. This should be considered when interpreting the overall positivity of the baseline attitudes.

The study was conducted in two Finnish wellbeing services counties with their own organisational structures, resources, and stages of digital transformation. These contextual factors differ from those of other regions or health systems, and the results should therefore be interpreted with awareness of the specific organisational environment in which the research was conducted.

The timing of the qualitative interviews presents an additional limitation. Interviews were carried out shortly after the interruption, at a point when sensemaking processes were still emerging. Perceptions may have changed as new information became available or as organisational communication evolved. Long-term, longitudinal approaches would be required to examine how interpretations develop over time.

Finally, the study reflects a specific moment in the development of health care AI. Technological maturity and organisational readiness evolve rapidly, and professionals' attitudes and trust-related interpretations are likely to change as AI tools become more familiar and integrated into practice. The cross-sectional survey and the limited interview window, therefore, constrain causal inference and capture only an early stage of perception formation.

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Annexes

Annex A. Additional Tables

Table A.1 Descriptive Statistics and Theoretical Links of Attitude Items

Items measuring Attitudes toward AI		Mean	SD	Theoretical Link
1	The use of AI in social and health care has advantages (e.g., improving continuity of patient care, reducing waiting times).	3.20	0.66	PU (TAM), PE (UTAUT)
2	I have a positive attitude toward the use of AI, even though I have to evaluate its reliability at the same time.	3.49	0.53	ATT (TAM) TR
3	Artificial intelligence can be used to improve the consistency of care needs assessments.	3.35	0.63	PU (TAM)
4	Using AI increases the efficiency of my work and improves my performance.	3.15	0.67	PU (TAM), PE (UTAUT)
5	I am concerned about the impact of AI on work ethics, customer and patient safety, privacy, and/or data protection. *(reversed)*	2.53	0.78	PR (Extended TAM) TR
6	I don't see AI bringing any added value to my work or its results.	1.81	0.73	PU (TAM)
7	An employee who uses AI is more efficient than an employee who does not use AI.	2.55	0.72	PU (TAM), PE (UTAUT)
8	Using AI in health care is easy and hassle-free.	2.44	0.84	PEOU (TAM), EE (UTAUT)
9	The use of AI brings more flexibility to my work and reduces my workload and stress.	2.68	0.76	PU (TAM)
10	AI has potential applications in my field of expertise.	3.12	0.66	PU (TAM)
11	AI can help predict patients' care needs and prevent diseases.	2.92	0.71	PU (TAM)
12	The use of AI can reduce administrative work and free up time for patient care.	3.03	0.66	PU (TAM)
13	The use of AI improves the quality of my work and reduces the number of errors (e.g., errors in assessing treatment needs or diagnoses).	2.85	0.61	PU (TAM), PE (UTAUT) TR
14	I am confident that the treatment recommendations made by the AI system are at least as good as, if not better than, those made by humans.	2.52	0.70	PU (TAM) TR
15	I will use artificial intelligence to support my work in the future.	3.29	0.69	BI (TAM)
16	AI can help reduce labour shortages in social and health care.	2.29	0.88	PU (TAM)
17	I consider AI to be valuable in terms of social and health care education, services, and research.	3.07	0.79	PU (TAM)
18	AI technologies can be used effectively and appropriately in the provision of social and health care services.	3.09	0.64	PU (TAM) TR
19	In the future, artificial intelligence may completely replace human labour.	1.17	0.55	PR (Extended TAM)

Note. N = 75. Items rated on a Likert scale (1-4); higher values indicate stronger agreement. Scores of items 5 and 6 were reversed before the analysis. ATT = Attitude towards using; BI = Behavioral intention to use; EE = Effort expectancy; PU = Perceived usefulness; PE = Performance expectancy; PEOU = Perceived Ease of Use. PR = Perceived Risk; The theoretical labels indicate conceptual links to domains in TAM, UTAUT, the extended TAM, or trust literature (TR).

Table A.2 Perceived AI Competence Survey Items

Items measuring Perceived AI Competence		Mean	SD
1	I am motivated to try artificial intelligence in my work.	3.60	0.52
2	I am familiar with best practices for using artificial intelligence in social and health care.	2.12	0.91
3	I can evaluate the reliability and accuracy of content provided by artificial intelligence.	2.89	0.85
4	I have the necessary knowledge to use AI-based systems.	2.41	1.04
5	I have gained a deeper understanding of the use of artificial intelligence in social and health care.	1.75	0.95
6	I am ready to learn more about using artificial intelligence in my work.	3.63	0.49
7	Learning to use artificial intelligence is easy for me.	3.04	0.89
8	I feel that I have sufficient support and training to implement artificial intelligence.	2.43	1.09
9	The introduction of artificial intelligence has a positive impact on my professional skills.	3.17	0.72

Note. N = 75. Items rated on a Likert scale (1-4); higher values indicate higher agreement.