JÖNKÖPING UNIVERSITY
*School of Engineering*

Doctoral Thesis

# Socio-Technical Problem-Understanding in AI Integration Projects

Alice Mohlin

Jönköping University
School of Engineering
Dissertation Series No. 108 • 2026

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Doctoral thesis in Industrial Engineering and Management

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# Abstract

Integrating artificial intelligence (AI) into organisational practices involves more than developing suitable technical solutions; it also requires understanding the organisational problems AI initiatives are intended to address and the socio-technical relationships involved. However, organisational problems are not necessarily fully understood from the outset and may evolve as new knowledge and technological possibilities emerge. Against this background, this thesis explores how socio-technical problem-understanding unfolds in practice and what shapes its development during AI integration projects. Adopting a pragmatist perspective and a constructivist grounded theory methodology, the research draws on empirical studies of exploratory AI integration projects involving predictive modelling in three manufacturing companies. Data were collected through observations and interviews and analysed through constructivist grounded theory procedures.

The study generated three main findings. First, socio-technical problem-understanding unfolds as an emergent, recursive, and directional process, in which temporary anchors enable provisional understandings that guide subsequent inquiry and may progressively direct attention different aspects of the problem. Second, socio-technical problem-understanding concerns the constitutive relationships among technology, organisation, people, and processes, whose meaning emerges from their interrelations within the organisational problem. Third, the conditions under which AI integration projects are organised shape the development and direction of problem-understanding by influencing the space within which socio-technical problem-understanding can emerge, while these emerging understandings may, in turn, create new requirements for how continued inquiry is organised.

Through these findings, the thesis contributes an integrated, constructivist-grounded theory explaining socio-technical problem-understanding in AI integration projects and offers a practical framework to support continuous inquiry into organisational problems and their socio-technical relationships.

**Keywords:** Socio-technical, problem-understanding, AI integration, AI projects, constructivist grounded theory, manufacturing

# Sammanfattning

Att integrera artificiell intelligens (AI) i organisationer handlar om mer än att utveckla tekniska lösningar; det kräver också förståelse för de organisatoriska problem som AI-initiativ syftar till att lösa och deras sociotekniska relationer. Dessa problem är dock inte nödvändigtvis fullt förstådda från början, utan kan utvecklas i takt med att ny kunskap och tekniska möjligheter växer fram. Mot denna bakgrund undersöker avhandlingen hur socioteknisk problemförståelse utvecklas i praktiken och vad som formar denna utveckling i AI-integrationsprojekt. Med utgångspunkt i pragmatism och konstruktivistiskt grundad teori bygger studien på observationer och intervjuer från utforskande AI-projekt med prediktiv modellering i tre tillverkande företag.

Studien resulterade i tre huvudsakliga resultat. För det första utvecklas socioteknisk problemförståelse genom en framväxande, rekursiv och riktad process, där tillfälliga hållpunkter möjliggör preliminära förståelser som vägleder fortsatt utforskande och gradvis kan rikta uppmärksamheten mot olika aspekter av problemet. För det andra handlar socioteknisk problemförståelse om de konstitutiva relationerna mellan teknik, organisation, människor och processer, vars innebörd framträder genom deras inbördes relationer i kontexten av det organisatoriska problemet. För det tredje formar de förutsättningar under vilka AI-integrationsprojekt organiseras problemförståelsens utveckling och inriktning genom att påverka utrymmet för socioteknisk problemförståelse att växa. Samtidigt kan dessa framväxande förståelser i sin tur skapa nya behov av hur det fortsatta utforskandet ska organiseras.

Utifrån dessa resultat bidrar avhandlingen med en integrerad konstruktivistiskt grundad teori som förklarar socioteknisk problemförståelse i AI-integrationsprojekt. Den presenterar även ett praktiskt ramverk som stödjer kontinuerligt utforskande av organisatoriska problem och deras sociotekniska relationer, inklusive anpassning av projektets organisering i takt med att förståelsen utvecklas.

**Nyckelord:** Socioteknik, problemförståelse, AI-integration, AI-projekt, konstruktivistiskt grundad teori, tillverkningsindustri.

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# 1. Introduction

*This chapter introduces the research problem and the study's motivations. It situates the research within the context of AI integration, presents the purpose and research questions, outlines the thesis's scope and delimitations, and concludes with an overview of its structure.*

## 1.1. The socio-technical and problem-related challenges of AI integration

Artificial intelligence (AI) is increasingly seen as a means of addressing organisational problems through automation, data-driven insights, and new forms of decision support (Davenport & Ronanki, 2018). Over the past decade, AI has been linked to far-reaching expectations about productivity and the transformation of work, including changes to occupational tasks and employment (Brynjolfsson et al., 2018; Frey & Osborne, 2017; Szczepański, 2019). However, integrating AI into an organisation involves more than introducing new technological capabilities; it also raises cognitive, relational, and structural challenges in integrating it into organisational work practices (Makarius et al., 2020).

Despite increasing investments in AI and growing organisational ambitions, many organisations struggle to realise the expected benefits of AI initiatives (Davenport & Ronanki, 2018; Fountaine et al., 2019). Evidence of these difficulties appears in both academic research and industry reports, which consistently point to challenges in translating

AI initiatives into broader organisational use and business value. For example, PwC (2021) reported that only a quarter of surveyed US companies had achieved widespread AI adoption, while most were barely breaking even on their AI investments. More recent findings from MIT Project NANDA and McKinsey similarly highlight that many organisations are still struggling to generate sustained business value from AI initiatives (Challapally et al., 2025; Singla et al., 2025). While these challenges are partly associated with issues such as data infrastructure, capabilities, and organisational arrangements (Haefner et al., 2023), they also raise broader questions about a narrower aspect of the challenge: how organisations develop an understanding of the organisational problems that AI initiatives are intended to address.

Integrating AI into organisations involves more than developing and implementing technological solutions. Research on AI integration has therefore increasingly emphasised the importance of socio-technical approaches, both in implementation practices and in how the final technology is intended to be used, recognising that successful integration requires attention to technological capabilities in relation to the organisational settings in which they are developed and will be used (Jarrahi, 2018; Makarius et al., 2020; Jarrahi et al., 2023). Empirical studies and literature reviews further highlight the importance of organisational readiness, collaboration between technical and business expertise, data infrastructure, organisational capabilities, and the coordination of tasks and processes when integrating AI into existing processes and organisational activities (Niehaus & Wiesche, 2021; Uren

& Edwards, 2023; Haefner et al., 2023; Lee et al., 2023; Romeo & Lacko, 2026).

Alongside these socio-technical considerations, research emphasises the importance of aligning AI initiatives with meaningful organisational problems and business needs. Rather than treating AI primarily as a technological opportunity, organisations are encouraged to identify relevant business applications, align initiatives with organisational priorities, and consider how AI capabilities might contribute to value creation (Davenport & Ronanki, 2018; Fountaine et al., 2019). However, this is easier said than done. Organisational problems are often complex and embedded in broader socio-technical contexts, making it difficult to determine how they can be meaningfully addressed through AI (Selbst et al., 2019; Passi & Sengers, 2020; Adobor, 2026).

Moreover, organisational problems are not necessarily clearly defined or fully understood from the outset. Research on innovation and problem framing suggests that problems may be uncertain, open-ended, and subject to reinterpretation as understanding evolves (Koen et al., 2001; Reid & de Brentani, 2004; Dorst, 2011; Magistretti et al., 2025). Problem and solution development may also be intertwined rather than sequential (von Hippel & von Krogh, 2016). Different perspectives shape organisational decision-making and problem framing and can influence subsequent courses of action (Cohen et al., 1972; Vaccaro et al., 2011). These complexities are also evident regarding AI integration:

translating organisational concerns into technically addressable problems requires interpretation and negotiation, while technical representations may leave important socio-technical relationships insufficiently considered (Passi & Barocas, 2019; Selbst et al., 2019). Together, these perspectives suggest that the organisational problems addressed through AI may be uncertain, understood in different ways, and continually revised as organisations explore the relationships between the social and technical aspects of the problem.

## 1.2. Previous research and research motivations: What we know and do not know about socio-technical problem-understanding in AI integration

The research presented in this thesis is situated within Industrial Engineering and Management, bringing research on the activity of understanding a problem (hereafter referred to as problem-understanding) in technology integration into conversation with research on the socio-technical challenges in AI integration, with a focus on the manufacturing context. As an initial step in the research presented in this thesis, a scoping review of advanced technology-related problem-solving in manufacturing was conducted (Mohlin, 2023). The review identified a strong emphasis on technological methods, implementation, and solution development, with comparatively less attention to the problems the technology is meant to address. Integrating digital technologies in manufacturing involves

aligning technological capabilities with existing production processes, organisational structures, and work practices (Chirumalla et al., 2025). While previous research shows that organisational problems are often uncertain, evolving, and open to different interpretations (Koen et al., 2001; Reid & de Brentani, 2004; Dorst, 2011; Magistretti et al., 2025), and integrating AI requires understanding and coordinating complex relationships between technology, people, organisational conditions, and work processes (Niehaus & Wiesche, 2021; Uren & Edwards, 2023; Haefner et al., 2023; Lee et al., 2023; Romeo & Lacko, 2026), this raises questions about how the interplay between these factors unfolds in practice.

### *1.2.1. What is meant by socio-technical*

Previous research has increasingly emphasised the socio-technical nature of AI integration from multiple perspectives. Makarius et al. (2020) conceptualise AI integration as a socio-technical process encompassing cognitive, relational, and structural complexities, and introduce the concept of socio-technical capital to describe the value generated by the effective integration of AI systems and employees. Similarly, Jarrahi et al. (2023) highlight the importance of human involvement, complementary capabilities, and the evolving relationships between human and technological agency during AI integration.

This socio-technical emphasis is further reflected in research examining the organisational requirements and challenges of AI implementation.

Drawing on organisational experiences of implementing and scaling AI, Haefner et al. (2023) identify technical and social components that support AI integration, including data infrastructure, organisational capabilities, expertise, and organisational structures, also providing a framework that shows how organisational requirements evolve as AI initiatives develop. Similarly, Lee et al. (2023), through a systematic literature review of AI implementation research, identify organisational, technological, information systems, and people-related dimensions that illustrate the range of interdependent conditions associated with AI implementation. Fountaine et al. (2019), drawing on organisational experience and management-oriented analysis, further emphasise cross-functional collaboration, organisational alignment, and the development of the capabilities needed to integrate AI into organisational activities.

Furthermore, Uren and Edwards (2023), in a qualitative study of AI experts across research, development, and business functions, investigate organisational readiness for AI adoption. Building on a people, processes, and technology perspective, their findings identify data readiness as an additional dimension and demonstrate the importance of connecting technical and business functions throughout the adoption process. Likewise, Dwivedi et al. (2021), through a multidisciplinary synthesis of perspectives on AI, identify challenges that extend beyond technological performance to include organisational, managerial, social, and policy-related considerations.

Taken together, this body of literature illustrates that AI integration is a socio-technical challenge spanning multiple aspects of technology development, introduction, and integration, in which technological capabilities must be considered alongside organisational conditions, data, and work practices. However, integration challenges remain. Building on these insights, there is value in further exploring how organisational actors develop an understanding of these interrelationships in practice, particularly how socio-technical considerations are identified, interpreted, and linked to the organisational problems being addressed.

### *1.2.2. How problems are approached and understood*

The preceding scoping review of advanced technology-related problem-solving in manufacturing found that research has primarily focused on technological solutions and their application, with comparatively less attention to the problems addressed (Mohlin, 2023). A similar emphasis on solution development rather than problem identification has been highlighted in AI research by Sturm et al. (2021).

A second research motivation, therefore, concerns the organisational problems driving AI initiatives, which empirical research and industry surveys indicate are difficult to understand in terms of their potential and intended value. Although published in 2018, the influential study by Davenport and Ronanki (2018), drawing on an examination of 152 AI projects and a Deloitte survey of 250 executives, reported that 47%

of executives surveyed experienced difficulties integrating AI into existing processes and systems. Westenberger et al. (2022) support this, as qualitative interviews with AI experts across different industries investigated factors contributing to AI project failure and identified misunderstandings of AI capabilities, unrealistic expectations, and use-case-related difficulties, including unclear organisational value, as critical factors. Together, these findings indicate that organisations face challenges in understanding the organisational problems that AI initiatives are intended to address.

Empirical research has also highlighted the challenges involved in translating organisational needs into technically actionable problems. Passi and Barocas (2019), through ethnographic research in a corporate data science setting, demonstrate how translating organisational objectives into data science problems involves negotiation, interpretation, and discretionary judgments, rather than being straightforward or predetermined; these decisions shape which problems become technically actionable and raise important questions about the consequences of particular problem formulations. In relation to that study, Passi and Sengers (2020) also investigated how practitioners establish and negotiate what data science systems should do, how they should function, and how their performance should be evaluated. Their findings show that these understandings are continually reshaped by existing technologies, emerging development challenges, and negotiations between business objectives and technical considerations, highlighting the evolving, socio-technical nature of

these challenges. These findings align with broader research on problem-solving and innovation, which recognises that problems may initially be ambiguous (Frensch & Funke, 1995), that problem framing and solution development can be interconnected (Dorst, 2011; von Hippel & von Krogh, 2016), and that problem representations may evolve through exploration and the development of new knowledge (Magistretti et al., 2025).

Taken together, this body of research highlights the challenges of understanding and addressing organisational problems in AI integration. Previous research has examined how meaningful organisational problems and needs are identified and how organisational objectives are translated into technically actionable problems. However, organisational problems are not necessarily fixed or fully understood from the outset, but may evolve as new knowledge, perspectives, and technological possibilities emerge. This raises further questions about how such evolving problem-understanding unfolds in practice, and about what shapes its development in AI integration initiatives.

### *1.2.3. How socio-technical problem-understanding unfolds in practice*

A third consideration therefore concerns the need for a better understanding of how socio-technical problem-understanding unfolds in practice during AI integration. Although previous research has identified important socio-technical considerations and challenges

associated with problem formulation, empirical studies also highlight the difficulties of addressing them in ongoing development activities. Hopf et al. (2023), drawing on an investigation of 55 organisational AI projects, identify tensions between expectations of structured and predictable development and the exploratory, iterative nature of data science activities. Similarly, de Mast and Lokkerbol (2024), through the development and application of a problem-structuring approach across data-analytic projects, highlight the difficulties of translating organisational objectives into analytical problems and the limited guidance provided by established frameworks such as CRISP-DM. Adobor (2026), from a conceptual perspective, further identifies the risk of *AI solutionism*, highlighting how this can emerge through the oversimplification of complex organisational problems and the momentum of AI adoption, potentially reinforcing a focus on technical solutions at the expense of broader organisational needs.

Research on organisational decision-making and innovation offers further reason to examine how these challenges unfold in practice. Cohen et al. (1972), through their garbage can model, illustrate how organisational problems, solutions, and participants may become connected in ways that do not follow a linear decision-making process. Vaccaro et al. (2011), in an empirical study of virtual design in the automotive industry, demonstrate how problem framing influences the use of technological tools and subsequent innovation activities. These contributions suggest that understanding organisational problems

cannot necessarily be separated from the activities, interactions, and technological possibilities through which they are approached.

Moreover, previous research on digital transformation emphasises the importance of innovation capabilities, continuous learning, collaboration, and adaptability when navigating technological change (Sousa & Rocha, 2019). More specifically, Eklöf et al. (2024), through an action research study of AI implementation, demonstrate how an agile and experimental approach, characterised by flexibility and collaboration, enabled a project team to make progress and adapt to changing requirements and unforeseen challenges.

Collectively, these studies highlight the practical challenges of AI integration, including translating organisational needs into technological development, navigating uncertainty, and coordinating diverse forms of knowledge and expertise. Building on these insights, further research is needed to understand how organisational actors work with problems that are not fully understood from the outset but continue to evolve with socio-technical considerations during AI integration. This involves examining how the organisational problem is collectively interpreted and revised through an emerging process, how its socio-technical relationships are identified and explored, and how this ongoing process of problem-understanding unfolds within the practical conditions of AI integration initiatives. Together, these considerations underscore the need for practice-near empirical research on the socio-technical problem-understanding during AI integration initiatives.

## 1.3. Purpose and research questions

While previous research has established the importance of socio-technical considerations in AI integration, highlighted challenges in understanding the organisational problems that AI initiatives are intended to address, and shown that these understandings may evolve over time, there remains a need for an integrated perspective that explains how organisational problems are understood, how their socio-technical relationships are explored, and how problem-understanding develops throughout AI integration initiatives. Together, these three motivations define the focus of this thesis. Its purpose is to explore and explain how socio-technical problem-understanding unfolds in practice and what shapes its development in AI integration projects by constructing an empirically grounded theory. The following research questions guide the study:

**RQ1:** How does socio-technical problem-understanding unfold in practice within AI integration projects?

**RQ2:** What shapes the development of socio-technical problem-understanding in AI integration projects?

In extension, by addressing this purpose and answering the research questions, this thesis aims to develop a framework that provides practical guidance for organisations undertaking AI initiatives.

## 1.4. Research context, thesis scope and delimitations

The scope of this thesis is limited to socio-technical problem-understanding in AI integration projects in manufacturing companies that use predictive modelling to address organisational problems. Yan et al. (2025), through a review of human-centric AI in industrial settings, highlight the need to move beyond technology-centred approaches towards AI systems that complement human capabilities and support human involvement in industrial activities. Similarly, research on manufacturing digitalisation has demonstrated the importance of shared understanding and collaboration when introducing new technologies into established organisational practices (Thun et al., 2022). Therefore, manufacturing organisations provide a particularly relevant setting for this research, as AI integration often involves connecting technological possibilities with existing processes, specialised expertise, and organisational practices, making the socio-technical nature of problem-understanding especially visible.

In this thesis, the term *organisational problem* is used in accordance with the broader problem-solving literature, in which a problem exists whenever there is a desired future state and no immediately known path to reach it (Newell & Simon, 1972). The term is used broadly to encompass what AI integration research frequently describes as *business problems*, *business needs,* or *use case*, that is, situations in which organisations seek to improve, optimise, predict, or otherwise

create value through AI initiatives (Davenport & Ronanki, 2018; Fountaine et al., 2019). Consequently, the thesis defines *organisational problems* as situations in which an organisation seeks to improve, change, optimise, predict, or create value but has not yet determined how to achieve that outcome.

The empirical studies focus on how socio-technical problem-understanding unfolds in AI integration projects rather than on the technical development or evaluation of the AI models within those projects. Although the empirical context involves extensive work with predictive modelling and data-driven decision support, the thesis centres on the organisational work surrounding these initiatives. It does not evaluate technical performance, compare technical solutions, or seek to generalise across all forms of AI integration. Although the empirical studies focus on predictive modelling initiatives in manufacturing organisations, the thesis adopts the broader term *AI integration* because predictive modelling represents one form of AI application and because the research aims to contribute to discussions on AI integration more broadly, referring to AI applications for business needs, while remaining analytically grounded in the specific empirical context studied.

The thesis is also specifically concerned with problem-understanding rather than problem-solving as a whole. While these processes are closely connected, the analytical focus is on socio-technical problem-understanding and how it unfolds in practice. It does not draw attention

to potential solutions or their implementations, although the findings may have implications for subsequent development, implementation, and scaling activities.

## 1.5. Thesis outline

This thesis consists of seven chapters. *Chapter 1* introduces the research problem, purpose, research questions, and the study's positioning. *Chapter 2* presents the theoretical and conceptual foundations. *Chapter 3* describes the research design, methodology, and research process. *Chapters 4* and *5* present the results from the observation and interview studies, respectively. *Chapter 6* integrates the results theoretically and answers the research questions. *Chapter 7* discusses the findings, contributions, limitations, and implications for future research.

# 2. Theoretical and Conceptual Foundations

*This chapter sets out the thesis's theoretical and conceptual foundations. It introduces the philosophical foundation, elaborates the central concepts and develops a conceptual framework for studying socio-technical problem-understanding in AI integration projects.*

## 2.1. Pragmatism as the philosophical foundation for studying socio-technical problem-understanding

To address the objectives of studying socio-technical problem-understanding close to practice, this research adopts a pragmatist philosophical foundation. Pragmatism originated in the work of Charles Sanders Peirce and William James and was subsequently developed by John Dewey, George Herbert Mead, and others (Cherryholmes, 1992; Creswell & Creswell, 2018). Central to pragmatism is the view that knowledge develops through action and experience, and that concepts are understood through their practical consequences (Cherryholmes, 1992). Pragmatism therefore provides a lens for examining how understanding develops in practice (Cherryholmes, 1992; Creswell & Creswell, 2018).

Dewey's (1938) account of inquiry highlights the importance of how problematic situations are understood and formulated. He argued that *"a problem well put is half-solved",* emphasising that the formulation of a problem guides what is considered relevant, which lines of inquiry are

pursued, and which possible solutions are explored. From this perspective, understanding a problem is not a preliminary step preceding action but an ongoing part of inquiry through which understandings are developed and revised (Morgan, 2020). Furthermore, pragmatism emphasises that because no two actors inherit the same set of preconditioned beliefs, inquiry is shaped by prior beliefs, which in turn influence how actors perceive problems and evaluate possible courses of action (Morgan, 2020). Given the evolving nature of organisational problems and the complexity of their socio-technical relationships, pragmatism provides a philosophical foundation for examining how socio-technical problem-understanding develops through inquiry and practical engagement during AI integration projects, and for identifying what shapes this development.

## 2.2. Conceptual foundations for socio-technical problem-understanding in AI integration

This section introduces and discusses the central concepts used throughout the thesis. The purpose is not to establish a predefined theoretical framework but to provide conceptual clarity regarding the phenomenon under examination.

### *2.2.1. Problem-solving research and its focus on solutions*

Problem-solving research has traditionally examined how problems are represented and how solutions are identified and developed (Newell & Simon, 1972; D'Zurilla & Goldfried, 1971). In research on advanced

technology-related problem-solving in manufacturing, this emphasis is particularly evident, with prior studies placing greater emphasis on technological solutions than on the initial activities of understanding and formulating problems (Mohlin, 2023).

Established problem-solving approaches commonly distinguish between activities concerned with identifying and defining problems and those directed towards generating, evaluating, and implementing solutions (D'Zurilla & Goldfried, 1971; Basadur et al., 1982). Within these stage-based conceptualisations, problem-understanding is primarily captured by activities in the earlier stages of the problem-solving process, although the approaches differ in how they conceptualise the relationships between stages. Figure 2.1 schematically illustrates this general progression from problem identification and definition towards solution development and implementation.

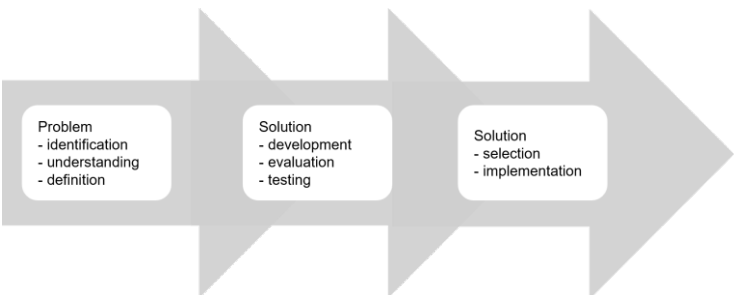


*Figure 2.1. Traditional stage-based view of problem-solving (author's synthesis based on Basadur, Graen, & Green, 1982; D'Zurilla & Goldfried, 1971).*

Although problem-solving research has recognised the importance of understanding and framing problems, this understanding is often considered in relation to the broader objective of developing solutions. For example, distinctions between well-structured, ill-structured, and wicked problems highlight how the nature and complexity of a problem influence the approaches needed to address it (Jonassen, 1997; Rittel & Webber, 1973).

Beyond the nature of the problem itself, the organisational conditions under which problem-solving takes place also influence how problems are approached. In their systematic literature review, Mohaghegh and Furlan (2020) identify factors such as time and information availability, collaborative culture, leadership, and the nature of the problem as important to the adoption of systematic problem-solving approaches. This is particularly relevant in manufacturing, where systematic problem-solving has long been central to production management, with established approaches such as the Toyota Production System and lean manufacturing emphasising structured problem identification, experimentation, and continuous improvement (Womack & Jones, 1996; Spear & Bowen, 1999).

Taken together, this body of literature shows that established problem-solving research does not disregard problems or problem-understanding themselves. Rather, it recognises their importance mainly in relation to how they contribute to problem-solving and the development of solutions. Alongside the solution-oriented emphasis identified in the

scoping review (Mohlin, 2023), this provides a basis for examining problem-understanding in AI integration more explicitly. Before doing so, however, it is necessary to clarify the concept around which these discussions revolve: what is a problem?

### *2.2.2. What is a problem?*

In general usage, Merriam-Webster defines a problem as *"a question raised for inquiry*, *consideration*, *or solution"*, while the Britannica Dictionary describes it as "*something difficult to deal with* or a *source of trouble or concern"* (Merriam-Webster, n.d.; Britannica Dictionary, n.d.). Together, these definitions present a problem both as something to be examined and as a condition experienced as difficult or in need of attention. In cognitive problem-solving research, a problem is commonly understood as a situation in which an actor seeks to reach a goal, but the means of doing so are not immediately apparent (Newell & Simon, 1972; Dunbar, 1998). Understanding a problem is therefore closely associated with developing a representation of the current situation, the desired outcome, and the obstacles or conditions that need to be addressed.

An alternative view, associated with pragmatist inquiry and reflective practice, understands problems as emerging through inquiry and problem-setting, rather than as fully specified at the outset (Dewey, 1938; Schön, 1983). Dewey distinguishes between a problematic situation and a problem formulated through inquiry, while Schön emphasises how practitioners, in interaction, identify which aspects of

a situation should be treated as problematic and addressed. From this perspective, what is understood as a problem and which aspects are considered relevant may be revised as actors explore a situation through action, reflect on their experiences, and reconsider their understanding in light of emerging insights and consequences. The same situation may be framed as different problems depending on actors' knowledge, assumptions, and concerns, and these framings may themselves evolve through continued inquiry (Dewey, 1938; Schön, 1983).

While the definition of organisational problems in the context of AI integration was acknowledged in Chapter 1, the preceding discussion provides a broader conceptual foundation for understanding what constitutes a problem. Drawing on this discussion, the thesis conceptualises organisational problems as situations in which an organisation seeks to improve, change, optimise, or create value, and where the nature and significance of the problem, as well as possible ways to address it, are not necessarily predefined but may evolve through ongoing action, interaction, and experience. While this discussion clarifies what is meant by a problem, it also raises a second question that is central to this thesis: what does it mean to understand a problem?

### *2.2.3. Understanding as an individual, collective and pragmatic phenomenon*

In general terms, understanding involves "grasping the meaning of something and interpreting or explaining it" (Britannica; Merriam-

Webster, n.d.). However, in research on problem-solving, understanding has been conceptualised in different ways. Cognitive approaches to problem-solving emphasise how individuals represent problem situations and use their knowledge to reason about possible actions and their consequences (Newell & Simon, 1972; Frensch & Funke, 1995). From this perspective, understanding is commonly conceptualised as the mental representations and knowledge structures that individuals use to interpret a problem situation and evaluate alternative courses of action.

In organisation studies, sensemaking perspectives emphasise that understanding develops through social interaction, as actors interpret situations based on prior experiences and revise their interpretations through communication and action (Weick, 1995; Weick et al., 2005), viewing understanding as collective. In organisational settings, actors may interpret the same situation differently because of their knowledge, assumptions, and experiences (Orlikowski & Gash, 1994). Through interaction, they may develop sufficient shared understanding to coordinate action without necessarily reaching complete agreement (Weick, 1995; Weick et al., 2005). Collective understanding can therefore be understood as the development of common ground that enables coordinated action despite differences in perspectives.

While these perspectives offer valuable insights into conceptualising understanding, this thesis primarily adopts a pragmatist view of how understanding develops through inquiry, reflection, and practical

engagement with problematic situations (Dewey, 1938; Morgan, 2020). From this perspective, actors draw on existing beliefs, respond to situations, and revise their understanding by reflecting on the consequences of their actions. However, as the research concerns problem-understanding within organisational teams, sensemaking perspectives provide a complementary emphasis on the social and collective dimensions of understanding (Weick, 1995; Weick et al., 2005).

### *2.2.4. Defining problem-understanding*

If a *problem* is understood as something that emerges and takes form through inquiry, and *understanding* is viewed as something that develops through action, interaction, and experience, what is left is to conceptualise them together as *problem-understanding.*

From a cognitive perspective, problem-understanding concerns how individuals interpret and make sense of a problem by developing mental representations of its relevant elements and relationships (Newell & Simon, 1972; Frensch & Funke, 1995). These representations are influenced by how problems are presented (Simon & Hayes, 1976) and may be constructed, refined, or restructured as individuals engage with them (Mumford et al., 1994). From these perspectives, understanding is primarily conceptualised as an individual cognitive accomplishment that shapes how a problem is approached and which actions are considered possible.

From a social perspective, problems are not necessarily objectively given but are understood and framed through interpretation and interaction. Schön (1983) distinguishes problem setting, arguing that different actors define problems by selecting and framing aspects of uncertain situations. Consequently, different experiences, assumptions, and knowledge may yield different understandings of the same situation, and, from a collective perspective, problem-understanding develops as actors interpret and negotiate these differences. For example, research on technological frames shows how organisational groups interpret technology through different assumptions, expectations, and knowledge (Orlikowski & Gash, 1994), while sensemaking research emphasises how meaning develops through social interaction and action (Weick, 1995; Weick et al., 2005). Collective understanding therefore need not entail consensus, as actors may coordinate their actions despite differing interpretations (Weick, 1995).

The pragmatist perspective places greater emphasis on how understanding develops and changes through practical engagement with problematic situations (Dewey, 1938; Morgan, 2020). Accordingly, problem-understanding is provisional and subject to revision as actors encounter new experiences, evaluate the consequences of their actions, and reconsider previous assumptions. Action is not merely a consequence of understanding but also a means by which understanding develops (Morgan, 2020). An important part of this conceptualisation is that these actions also produce understandings

that guide subsequent action (Dewey, 1938; Morgan, 2020). Such understandings may provide direction for action while remaining open to revision through continued inquiry (Dewey, 1938; Morgan, 2020). Problem-understanding and problem-solving are therefore closely intertwined, as both the interpretation of a problem and possible courses of action may evolve throughout the process of inquiry.

Taken together, the literature conceptualises problem-understanding from multiple perspectives, including cognitive representation, socially situated interpretation, collective meaning-making, and practical inquiry. While these perspectives illuminate what understanding is and how it is shaped, this thesis primarily adopts a pragmatist perspective, emphasising how understanding develops through action, interaction, and ongoing inquiry in practice (Dewey, 1938; Morgan, 2020). At the same time, recognising that problem-understanding is investigated within organisational groups, the thesis acknowledges its socially constructed character, as actors bring different expertise that shapes how organisational problems are collectively understood. Accordingly, problem-understanding is conceptualised as an ongoing process of inquiry through which actors develop, negotiate, test, and revise their understanding of problematic situations. In this thesis, inquiry refers to the ongoing actions of developing, negotiating, testing and revising understanding through action, interaction, and experience. Here, developing refers to the formation of understanding through experience and inquiry, negotiating the interaction between actors with different interpretations, testing by examining assumptions through action and

its consequences, and revising by reconsidering previous understandings in light of new experiences. Together, these activities reflect the ongoing and socially situated character of problem-understanding. Having established how problem-understanding is conceptualised, the next step is to clarify what is meant by socio-technical means in the context of this research. Therefore, the next concept under discussion is socio-technical systems thinking.

### *2.2.5. Socio-technical systems thinking*

The concept of socio-technical systems stems from the work of Trist and Bamforth (1951) in British coal mines, where their studies showed that introducing new technologies affected not only technical processes but also work patterns, collaboration, and organisational performance. Socio-technical perspectives emphasise that organisational work systems consist of interdependent social and technical elements that must be understood in relation to one another (Trist & Bamforth, 1951; Appelbaum, 1997; Klein, 2014). People, technologies, tasks, and organisational structures are interconnected, so changes to one element may have implications for others (Leavitt, 1965).

Socio-technical systems thinking has been conceptualised and visualised in different ways across research traditions and application areas, while maintaining a central emphasis on the interdependence of social and technical elements within organisational systems (Davis et al., 2014). Examples include Leavitt's (1965) four-element model and the hexagonal framework presented by Davis et al. (2014). Drawing on

this shared emphasis on interdependence, this thesis adopts four analytical categories, *organisation, people, process, and technology,* to examine socio-technical problem-understanding in AI integration, as illustrated in Figure 2.2.

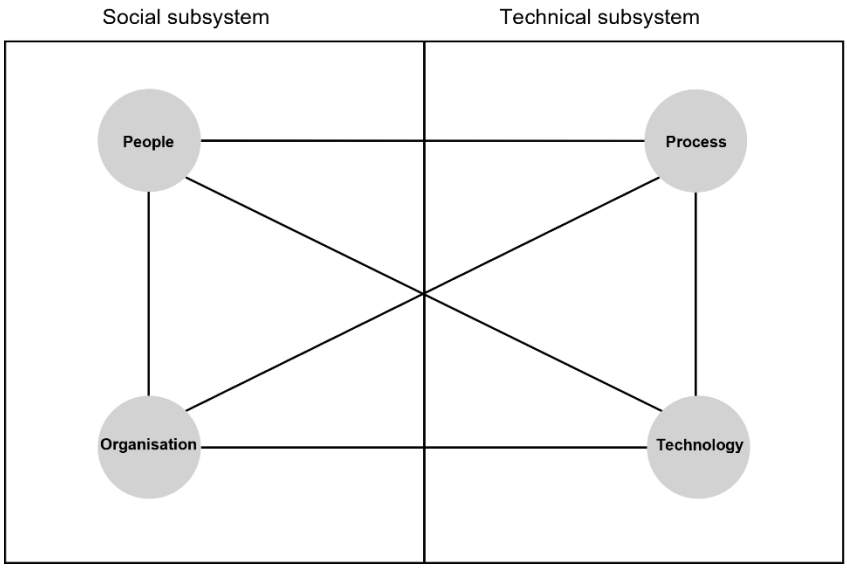


*Figure 2.2. Socio-technical systems thinking, based on Leavitt (1965) and Davis et al. (2014).*

Historically, socio-technical systems thinking has been a key perspective for understanding work design, organisational change, and the relationship between people and technology (Appelbaum, 1997; Klein, 2014). A central principle is joint optimisation, which emphasises that social and technical systems should be considered and designed together rather than optimised independently. This requires a dual focus on both dimensions, recognising their interdependence and the potential trade-offs in organisational design (Fox, 1995;

Appelbaum, 1997). Consequently, changes to one part of the system may affect other parts, making it important to understand how technological, human, and organisational elements interact as a whole (Fox, 1995). Hence, in practice, the socio-technical perspective recognises that challenges with, for example, technology implementation and integration arise when technology and organisational work practices are misaligned (Davis et al., 2014).

### Sociomateriality

While socio-technical systems emphasise the interdependence of social and technical elements, sociomateriality offers a different way of conceptualising their relationship. Traditional socio-technical perspectives generally treat the social and technical as distinct yet interdependent parts of an organisational system (Leavitt, 1965; Davis et al., 2014). Sociomateriality, by contrast, challenges the assumption that these elements exist independently of one another, emphasising that they are constituted through their ongoing relationships in practice (Orlikowski, 2007; Orlikowski & Scott, 2008; Orlikowski, 2010). In sociomateriality, materiality refers to the material aspects of organisational life, such as technologies, tools, and infrastructures, which are not merely passive objects but actively shape organisational practices and outcomes (Orlikowski, 2007; Orlikowski & Scott, 2008).

Central to sociomateriality is the notion of constitutive entanglement, which holds that social and material aspects do not merely interact as independent elements but are mutually constituted through practice

(Orlikowski, 2007; Orlikowski & Scott, 2008). From this perspective, technologies do not possess fixed organisational meanings or consequences independent of their use. Rather, their significance and effects emerge through the practices, relations, and material arrangements in which they are enacted (Orlikowski, 2007; Orlikowski, 2010). Hence, sociomaterial practices refer to everyday organisational activities in which social and material aspects are inseparably intertwined, shaping how work is carried out in practice (Orlikowski, 2007). Although distinguishing between social and technical aspects may be useful for analytical purposes, sociomateriality emphasises that such distinctions should not be mistaken for an actual separation in organisational practice (Orlikowski & Scott, 2008).

In this thesis, socio-technical systems thinking and sociomateriality offer complementary ways of examining problem-understanding in AI integration. Socio-technical systems thinking provides analytical categories for identifying relevant organisational, human, process-related, and technological aspects of a problem, while sociomateriality highlights how these aspects are interconnected and acquire meaning through practice in relation to the problem. This relational emphasis is also compatible with the thesis's pragmatist orientation towards action, experience, and inquiry. Rather than committing exclusively to either a socio-technical or sociomaterial perspective, the thesis remains open to what happens in practice and to how organisational actors identify, distinguish, and relate social and technical aspects as they develop their understanding of problems. This also reflects the exploratory nature of

the research and avoids assuming in advance which distinctions or relationships will prove meaningful in practice. Having established these conceptual foundations, the next subsection turns to the specific context of AI integration projects.

### *2.2.6. AI integration projects as a context for understanding socio-technical problem-understanding*

Artificial intelligence (AI) encompasses a broad range of technologies and approaches, including machine learning, deep learning, natural language processing, computer vision, expert systems, and robotics (Russell & Norvig, 2010). From an organisational perspective, Davenport and Ronanki (2018) distinguish three main applications of AI: process automation, which automates routine tasks; cognitive insight, which uses data and machine learning to identify patterns and generate predictions; and cognitive engagement, which supports interactions with customers and employees. In this way, specific AI technologies offer opportunities to augment human problem-solving capabilities. In a scoping review of 38 studies, Joksimovic et al. (2023) identified applications of AI that support the cognitive, metacognitive, social, and affective aspects of complex problem-solving, with the strongest research emphasis on cognitive support, particularly in relation to analysing information, identifying patterns, and supporting decision-making. Although this thesis does not aim to study the specifics of AI technologies or applications, the projects focus on predictive modelling, an application of cognitive insight in which data and machine learning are used to generate predictions that may support

organisational planning and decision-making (Davenport & Ronanki, 2018).

The introduction of AI into organisations has been examined through concepts such as adoption, implementation, and integration, with research highlighting the organisational challenges and changes associated with these processes (Raftopoulos, 2024; Romeo & Lacko, 2026). For conceptual clarity, this thesis distinguishes between AI adoption, the organisational uptake of AI; AI integration, the embedding of AI into organisational processes and work practices; and AI transformation, broader organisational changes associated with AI. The research focuses on AI integration, recognising that introducing AI involves more than developing or acquiring technological capabilities; it also entails examining how these capabilities relate to organisational needs, existing practices, and conditions.

Compared with "previous" technologies, AI introduces distinctive characteristics that may complicate its integration into organisational practices. In a conceptual paper, Berente et al. (2021) identify autonomy, learning, and inscrutability as three interrelated characteristics of AI, meaning that AI systems can operate with varying degrees of independence, learn from data, and produce outcomes that may be difficult to interpret or explain. Similarly, in a conceptual analysis of how learning algorithms may affect organisations, Faraj et al. (2018) argue that these technologies can transform organisational

expertise, reshape work practices and occupational boundaries, and introduce new forms of coordination and control.

When it comes to the practical organisational work of integrating AI, these initiatives are often pursued through pilots and experimental projects that explore technological possibilities and potential organisational value (Davenport & Ronanki, 2018; Fountaine et al., 2019), with the aim of scaling within the organisation. Projects can be understood as temporary forms of organising, characterised by bounded timeframes, specific tasks, and collective action (Lundin & Söderholm, 1995; Packendorff, 1995). Or, as Lundin and Söderholm (1995) distinguish, time, team, task and transition. Projects provide arrangements for coordinating activities, resources, and specialised expertise (Davies & Hobday, 2005) while remaining embedded in broader organisational contexts. The increasing reliance on projects to organise innovation and organisational change has been discussed in terms of projectification, referring to a shift towards project-based forms of organising and their growing influence on permanent organisational structures and practices (Midler, 1995; Gemünden et al., 2018; Sydow & Windeler, 2020).

Against this background, AI integration projects are understood in this thesis as temporary organisational arrangements in which actors collectively explore AI's potential in relation to organisational problems while developing their understanding of the social and technical conditions involved. This provides the empirical and organisational

context for examining how socio-technical problem-understanding unfolds in practice.

## 2.3. Conceptual integration: Socio-technical problem-understanding in AI integration projects

Taken together, the conceptual perspectives discussed in this chapter provide a foundation for examining socio-technical problem-understanding in AI integration projects. From a pragmatist perspective, problem-understanding develops through action, interaction, and experience rather than through detached analysis alone (Dewey, 1938; Morgan, 2020). Socio-technical systems thinking highlights that this inquiry may involve organisational, people, process, and technological aspects, as well as the relationships among them (Leavitt, 1965; Davis et al., 2014; Orlikowski, 2007; Orlikowski & Scott, 2008). Building on these perspectives, this thesis adopts organisation, people, process, and technology as analytical categories for examining socio-technical problem-understanding in AI integration projects. Socio-technical problem-understanding is therefore conceptualised as the ongoing process through which organisational actors develop and revise their understanding of organisational problems by exploring organisational, people, process, and technological aspects and their relationships in

practice.

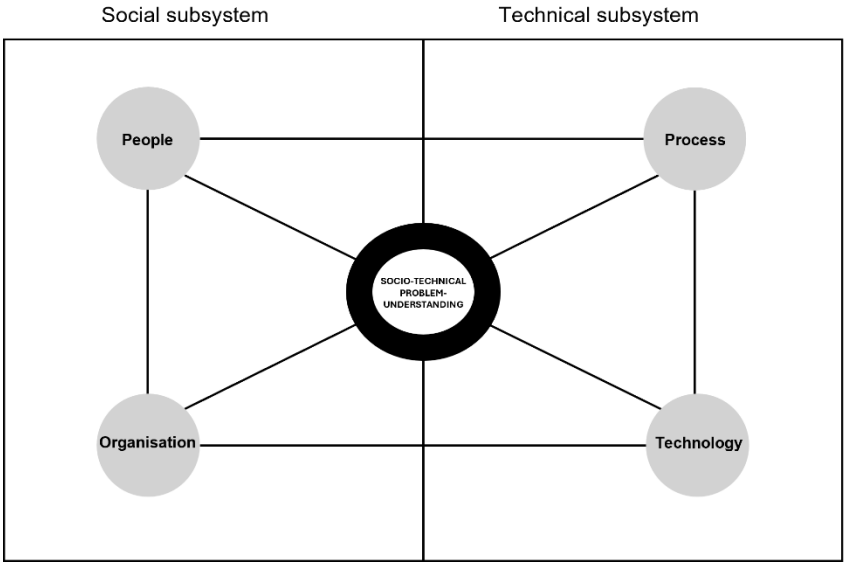


*Figure 2.3 Conceptualisation of socio-technical problem-understanding*

Figure 2.3 illustrates this conceptualisation. The four interconnected categories represent relevant areas of inquiry. Although the categories are presented separately for analytical purposes, they are not assumed to exist independently in practice. The figure therefore provides a conceptual starting point rather than a predefined model.

# 3. Methods in Theory and in Practice

*This chapter presents the methodological foundations of the research. It describes the research design, constructivist grounded theory approach, and overall research process, as well as the empirical context, data collection, and data analysis procedures. The chapter concludes with a discussion of research quality and ethical considerations.*

## 3.1. Research design

### *3.1.1. Methodological implications of pragmatism*

Beyond informing the study's philosophical foundation, pragmatism also shaped how the research was conducted, how the phenomenon was approached, and how the findings were interpreted. First, it supported an iterative research process in which decisions about data collection, analysis, and engagement with the literature were revisited as new insights emerged. Rather than following a fully predetermined research design, some methodological choices were guided by the evolving understanding of the phenomenon and the consequences of earlier decisions (Dewey, 1938; Cherryholmes, 1992; Morgan, 2020).

Second, pragmatism shaped the conceptualisation of socio-technical problem-understanding as an ongoing rather than a fixed state, thereby guiding what was considered important during data collection. Drawing on the pragmatist emphasis on inquiry through action and experience (Dewey, 1938; Morgan, 2020), the analysis focused on problem-understanding unfolding as a consequence of the project teams' actions,

rather than assuming that such understanding existed prior to action. Third, pragmatism informed the interpretation of empirical findings and the development of theoretical explanations. Consistent with the pragmatist view of inquiry as an ongoing process in which understanding is developed and revised (Morgan, 2020), the theoretical analysis involved moving between empirical findings and existing literature to develop and refine explanations of how socio-technical problem-understanding unfolds and what shapes its development, further reflected in the methodological choices described below.

### *3.1.2. This research is abductive…*

First, this research adopted an abductive approach, moving iteratively between empirical observations and theoretical reasoning to develop and refine explanations of the phenomenon under study (Miles et al., 2014; Säfsten & Gustavsson, 2020). Abductive reasoning involves developing plausible explanations for observations that are not readily explained and reconsidering these explanations in light of further empirical and theoretical insights (Peirce, 1958, as cited in Charmaz, 2017). The abductive approach was adopted early in the research process, as it was considered particularly suitable for studying AI integration, an evolving field in which existing theoretical explanations and emerging organisational practices could inform one another.

### *3.1.3. …exploratory and explanatory…*

Second, this research is both exploratory and explanatory. It is exploratory because socio-technical problem-understanding in AI integration projects remains relatively underexplored, making an open-ended approach suitable for investigating how the phenomenon unfolds in practice. Rather than testing predefined hypotheses, the research seeks to identify and develop patterns and conceptual insights through close engagement with empirical material (Miles et al., 2014; Säfsten & Gustavsson, 2020). At the same time, the research has an explanatory ambition, seeking to move beyond describing empirical patterns towards developing an empirically grounded understanding of how socio-technical problem-understanding unfolds and what shapes its development. This reflects the distinction between description and explanation in qualitative analysis (Miles et al., 2014).

### *3.1.4. …and qualitative*

Finally, this research adopts a qualitative approach, focusing on project members' experiences, interpretations, and actions within their organisational contexts (Creswell & Creswell, 2018). Qualitative research is particularly well suited to examining socially situated processes in depth, enabling researchers to explore how actors interpret and engage with situations in practice rather than measuring predefined variables (Denzin & Lincoln, 2011). Qualitative research was therefore considered appropriate for investigating how socio-technical problem-understanding unfolded.

## 3.2. Research Approach

To guide the analysis and generation of theory from the empirical material, this research adopts constructivist grounded theory as an overall methodological approach. Classic grounded theory was developed by sociologists Glaser and Strauss (1967) in the 1960s as a means of generating theory through systematic data collection and analysis. It challenged the prevailing emphasis on testing existing theories and encouraged researchers to develop explanations grounded in empirical material rather than imposing preconceived theoretical categories (Glaser & Strauss, 1967; Charmaz, 2014). Grounded theory is therefore considered suitable when the aim is to explore new scientific territory and to understand social patterns in action without testing or explaining them using established theories (Denscombe, 2014).

Although grounded theory traditions differ in their philosophical assumptions and analytical procedures, they share several methodological principles. These include (1) everything is data, recognising that observations, interviews, interactions, and researcher reflections may inform the analysis; (2) an emergent research process, in which analytical categories and theoretical explanations are progressively developed and refined; (3) constant comparative analysis, involving ongoing comparisons between data, codes, and categories to identify similarities, differences, and conceptual relationships; and (4) theoretical sampling, in which decisions about further data collection

are guided by the need to develop and refine emerging theoretical categories (Charmaz, 2014; Denscombe, 2014).

However, the ideal of pure induction associated with classic grounded theory has been criticised on the grounds that researchers cannot enter the field free of prior knowledge and theoretical assumptions (Thornberg, 2012). Different grounded theory approaches have developed partly through debates about these assumptions and the researcher's role in generating knowledge (Charmaz, 2014). Instead, contemporary grounded theorists are not expected to go into a field with a blank mind for inductive purposes, but rather with a rigid set of ideas, and strive for a very high level of transparency (Denscombe, 2014). Since the introduction of Glaser and Strauss's (1967) grounded theory, the methodology has evolved into novel forms, including evolved grounded theory, informed grounded theory, constructivist grounded theory and more (Charmaz, 2005; Denscombe, 2014; Thornberg, 2012; Johnson & Walsh, 2019; Chun Tie et al., 2019). All the above stem from the same basic idea of systematic but flexible approaches for collecting and analysing qualitative data to build empirically grounded theory (Charmaz, 2005).

### *3.2.1. Constructivist Grounded Theory*

This research adopts constructivist grounded theory, which is closely rooted in the pragmatist tradition. The two share key assumptions about reality, knowledge, and action (Charmaz, 2014). In her 2017 article, Charmaz illustrates the connections between pragmatism and

constructivist grounded theory in a table, from which Table 3.1 below is adapted.

*Table 3.1 Pragmatism and constructivist grounded theory (adapted by Charmaz, 2017)*

| PRAGMATISM | CONSTRUCTIVIST GROUNDED THEORY |
|---|---|
| Views reality as social | Views reality as social |
| Assumes processes | Studies processes |
| Acknowledge multiple perspectives | Seeks multiple perspectives |
| Sees meanings and actions as emergent and as affecting each other | Studies emergent meanings and actions and how one affects the other |
| Provides the roots for a theory of action | Provides the methods for theorising action |

According to Charmaz (2017), both pragmatism and constructivist grounded theory regard reality as social and continuously emerging, with meaning and action intertwined and individuals as active, reflective agents within a fluid, evolving reality. Both also emphasise the importance of abductive reasoning, in which researchers move

iteratively between data and possible explanations to develop the most plausible theoretical understanding (Charmaz, 2017).

## 3.3. Research Process and Applying Constructivist Grounded Theory

Figure 3.1 illustrates the abductive, iterative, and interconnected research process underpinning the constructivist grounded theory study. The research began with initial field observations as part of a larger study examining readiness for AI transformation in manufacturing organisations. During these observations, problem-understanding emerged as a recurring challenge, drawing attention to the phenomenon. This initial insight prompted further engagement with relevant literature, including a scoping review of problem-solving and advanced technology integration (Mohlin, 2023).

Through an abductive movement between empirical observations and existing research, the research problem and key concepts were gradually clarified, providing the foundation for the subsequent research design. Phase I (observations) involved collecting and analysing observational data to initially explore how socio-technical problem-understanding unfolded in practice and what shaped its development. The material was analysed using initial, focused, and theoretical coding, supported by memo writing, constant comparison and the use of conceptual foundations as sensitising concepts in accordance with constructivist grounded theory procedure (Charmaz, 2005).

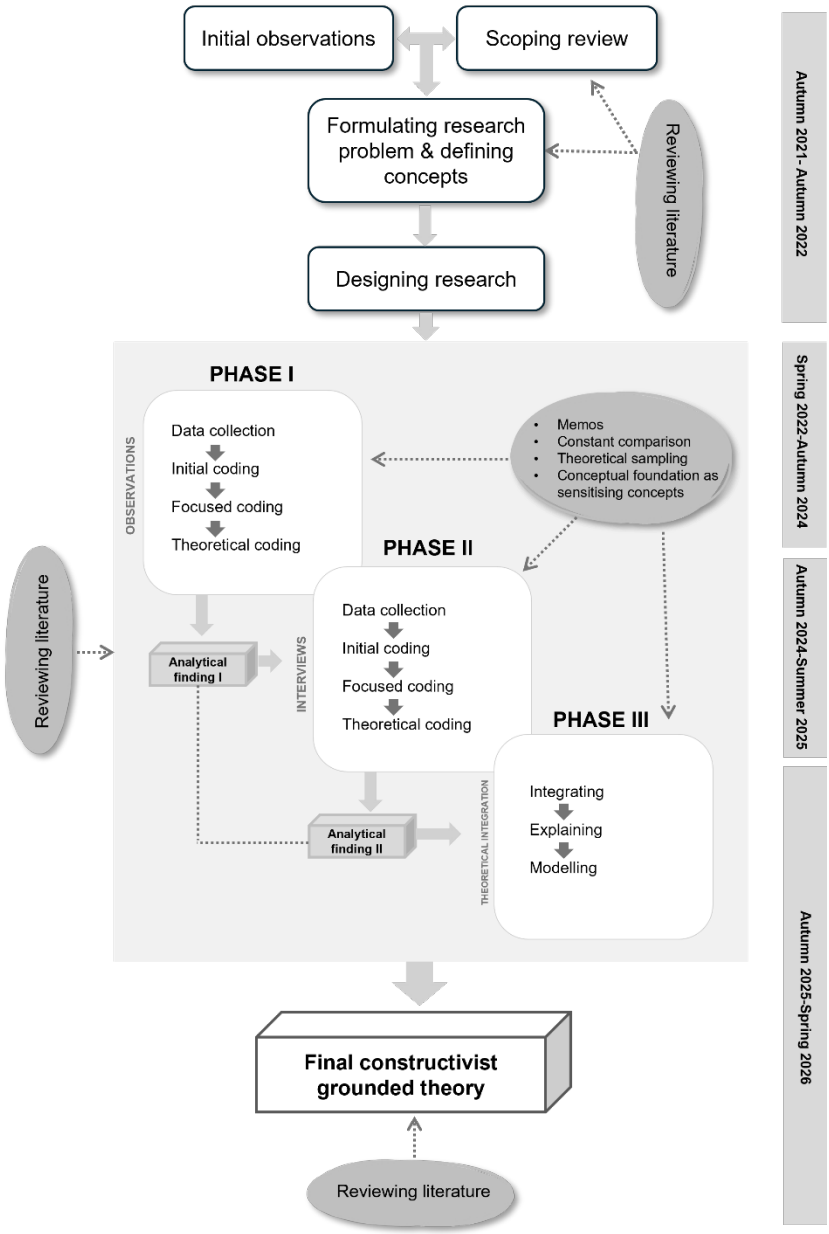


*Figure 3.1. Illustration of research process*

The analysis yielded analytical finding I, informing the analysis in the next phase. Phase II interviews were conducted to develop a deeper understanding of how socio-technical problem-understanding unfolded and what shaped its development by exploring project members' experiences, interpretations, and reasoning about their work. The analysis of the interview data built on the analytical insights developed in Phase I, using the same coding procedures and constant comparison to further develop and refine emerging categories. Throughout this process, the conceptual foundations were again used as sensitising concepts to support analytical questioning and interpretation without predetermining the findings. This iterative analysis resulted in analytical finding II, which complemented and extended the understanding developed through the observational study.

Phase III, theoretical integration, synthesised the two analytical findings to develop a more comprehensive theoretical explanation of socio-technical problem-understanding in AI integration projects. Building on the analytical findings from Phases I and II, the theoretical integration focused on identifying and explaining relationships between the findings at a higher level of abstraction, bringing them into dialogue with the conceptual foundations. These conceptualisations were thus used as a resource for theoretical interpretation and integration rather than as a predefined framework. This process yielded three theoretical findings, which were subsequently integrated into the final constructivist grounded theory.

### *3.3.1. Key constructivist grounded theory practices*

As shown in Figure 3.1, several key constructivist grounded theory practices were used throughout the research process.

#### Rich data

First, the quality of a constructivist grounded theory study depends on the *richness of the data* (Charmaz, 2005). To capture what is happening in the research setting, data collection must be iterative and guided by the emerging analysis, often requiring adjustments to explore new insights (Charmaz, 2005; 2017). In both observations and interviews, richness was "obtained" by being open to everything happening, maintaining an open, exploratory mind, and adopting the mindset that *"everything is data"*. Richness was thus pursued by remaining open to actions, interactions, accounts, and contextual information relevant to the emerging research focus, while documenting observations and analytical reflections in detail.

#### Memo-writing

In constructivist grounded theory, memo-writing is a central analytical activity that runs throughout the research process, supporting the development of theoretical concepts from empirical material (Charmaz, 2005; Lempert, 2007). Rather than merely describing empirical observations, memos provide a space for exploring interpretations, developing conceptual relationships, and moving towards greater theoretical abstraction (Lempert, 2007). They are typically written in a

flexible, exploratory manner, allowing analytical ideas to be developed and refined without requiring structured or polished accounts (Charmaz, 2005). Stern (2007) illustrates the importance of memo-writing in theory construction through the metaphor of data as the findings of theory and memos as the mortar connecting them.

In this research, memo-writing began with initial data collection and continued throughout the research process, as illustrated in Figure 3.1. In practice, this involved documenting analytical thoughts, questions, and emerging interpretations during data collection and analysis, from the first interactions with participating companies to the development of the final constructivist grounded theory model. Early memos posed questions such as *"What do they mean by value creation through AI, and who determines that value?"* and included reflections from observations such as *"Excitement about technology overshadows problem-understanding."* These memos provided a basis for exploring emerging ideas and progressively developing theoretical interpretations.

Naturally, the memos from the observation study were more "immature" and focused on exploratory questioning and positioning. As the research continued, the memos became increasingly analytical and narrow, addressing more abstract views of the empirical material. The memos were written by hand in notebooks, and later they were transferred into tables in MS Word. When the analysis procedures were

initiated, the memos were categorised into overarching themes to clarify their general implications.

Selected memos and the categories mentioned are presented in Appendix A and Appendix B. As memos were used dynamically, continuously revisited, and developed alongside the analysis, their role is reflected throughout the methodological account rather than documented individually at each stage in terms of content and function.

### Constant comparison

*Constant comparison* is also a central analytical strategy that drives the development of theory in constructivist grounded theory, and it involves continuously comparing data with data, data with codes, and codes with emerging categories to identify similarities, differences, and patterns, thereby making the analysis more integrated (Charmaz, 2005). In practice, this meant having the codes, memos, and categories "at hand" at every step of the analysis (when done analogously, all sheets of paper were present; when done digitally, all NVivo files were open). This procedure was greatly aided by detailed memo-writing, and as new insights emerged, they were iteratively checked against the memos, allowing categories to be refined continuously.

### Theoretical sampling

Another tool in constructivist grounded theory is *theoretical sampling*, which entails collecting additional data and steering the analysis in response to emerging analytical insights rather than predefined criteria

(Charmaz, 2005). As initial categories emerge through coding and memo-writing, the researcher actively seeks new data to elaborate, refine, and challenge them, focusing on variations and relationships (Charmaz, 2005). Theoretical sampling informed the research process primarily by directing analytical attention to questions and relationships that required further development. Following Phase I, the interviews were used to explore socio-technical problem-understanding in greater depth. Although the selection and collection of interview data were not determined solely by the emerging categories from the observations, the interview analysis was guided by the need to elaborate on, refine, and challenge the insights developed in Phase I.

### Researcher role transparency

In contrast to other grounded theory approaches, constructivist grounded theory positions the researcher as an active, central participant in the research process, with data and analysis understood to be co-constructed rather than discovered (Charmaz, 2005; 2008; 2017). In other words, the researcher's prior experiences and perspectives inevitably shape how data are generated, interpreted, and developed into theory. Table 3.2 below illustrates my role as a researcher in terms of prior knowledge and experience, its implications for the research process, and the considerations taken. It outlines my role as a researcher, drawing on prior knowledge and experience, and sets out the implications for the research process and the considerations taken. By consolidating these reflections into a single table, I aim to provide transparency about my position and potential influence without

repeatedly addressing them in subsequent sections. Nevertheless, these reflexive considerations were acknowledged throughout the research process, even when not explicitly discussed in the text.

*Table 3.2 My researcher role and implications on research*

| About myself as a researcher | Implication on research | Considerations taken |
|---|---|---|
| Limited professional experience in manufacturing industry and data science | Risk of not fully understanding technical details or industry-specific practices | Asked follow-up questions and relied on project members' explanations; compared across cases to avoid misinterpretations |
| Previous research in organisation studies | Strong focus on organising, structure, and social dynamics | Made sure not to overlook technical aspects; stayed close to what was in the data |
| Experience in project-based work | Tendency to see things as structured projects (phases, goals, steps) and interpret data in that way | Reflected on this in memos; questioned linear interpretations and stayed open to the messy and non-linear |
| Interest in pragmatism and socio-technical systems thinking | Risk of paying particular attention to processes, relationships and emerging understandings | Remained very strict in coding procedures to stay open to alternative interpretations |
| Prior knowledge of AI integration and socio-technical systems | Risk of seeing what I expected (preconceptions shaping coding and interpretation) | Actively used initial coding close to data and delayed abstraction |
| Familiarity with the research context (e.g. TARS project / similar settings) | Easier access and understanding, but risk of taking things for granted | Used constant comparison to challenge "obvious" interpretations and looked for variations and contradictions |
| Role as researcher vs. perceived expert by project members | Project members may adapt responses (e.g., emphasise technical aspects or "what sounds right") | Used open-ended questions, encouraged examples, and reflected on interaction dynamics in memos |

| | | |
|---|---|---|
| Interest in problem-understanding as a concept | Risk of steering analysis toward confirming its importance | Allowed categories to emerge before naming them, and only later connected to “problem-understanding” |

Charmaz (2005) writes that we are part of the world we study and of the data we generate, and therefore grounded theory is constructed through our interactions, experiences, and research practices, both past and present. By acknowledging and articulating the researcher’s role, the study’s transparency and credibility are strengthened, positioning the resulting theory as an interpretive, contextually grounded understanding rather than an objective account (Charmaz, 2005).

### How theory was used

Constructivist grounded theory offers an approach to theorising action and processes in which existing theoretical perspectives can inform the analysis without determining the emerging theoretical explanations (Charmaz, 2014). Consistent with this, the existing theoretical concepts were initially used as sensitising concepts rather than as predefined analytical categories (Charmaz, 2014). The conceptual foundations presented in Chapter 2 provided perspectives that informed analytical questioning and helped identify potentially relevant aspects of the empirical material, without determining the codes, categories, or findings. In other words, the analysis in Phases I and II was heavily empirically grounded, using theoretical concepts only to anchor emerging understandings.

During theoretical integration, the analytical findings engaged in deeper dialogue with the conceptual foundations, informing the interpretation and further development of the empirical insights and thereby supporting the construction of three theoretical findings and their corresponding models. These models were therefore not predefined applications of existing theory, but theoretical explanations developed through the interaction between empirical findings and sensitising concepts. In the final discussions, the three theoretical findings were examined in relation to one another and to previous research on AI integration to further refine their relationships and explanatory significance. Through this process, the final constructivist grounded theory was developed as an integrated explanation of how socio-technical problem-understanding unfolds, what it entails, and how its development is shaped by the conditions under which AI integration initiatives are organised. Accordingly, conceptual foundations and previous research played different but connected roles throughout the research process: sensitising the empirical analysis, supporting the development of theoretical findings and models, and informing their subsequent integration into the final grounded theory.

## 3.4. Research context: The TARS project

The research presented in this thesis was conducted within a larger research profile focused on the introduction of AI in the manufacturing industry, encompassing several projects examining data science, flows, and organisational aspects of AI transformation. The empirical studies

in this thesis were conducted by observing one of the data science projects, hereinafter referred to as the TARS project, which ran from 2022 to 2023 and explored the potential of using AI-based predictive modelling to support decision-making in manufacturing organisations.

Within the project, participating manufacturing companies collaborated closely with researchers to explore predictive modelling for selected, company-specific business cases. These cases addressed a range of organisational needs, from sales forecasting and operational planning to predicting which quotations were likely to result in orders and supporting pricing and dimensioning decisions. As this thesis focuses on socio-technical problem-understanding rather than the technical development or outcomes of individual projects, the specific details of each case are not examined in depth and will not be further acknowledged in the thesis. The project adopted a collaborative and exploratory approach, with cross-functional teams investigating how available data and predictive models could be used to address these business cases.

Throughout this thesis, *project members* refer to individuals involved in the projects under study, including company representatives and collaborating university researchers, whereas *project teams* refer to the teams collectively.

## 3.5. Phase I: Observations

The constructivist grounded theory study was conducted in three phases, two of which involved empirical data collection, beginning with observations of the participating companies' practices within the TARS project.

### *3.5.1. Observed organisations and project teams*

For the observations, three manufacturing companies that were part of the research profile and active in Sweden were followed in their AI integration efforts throughout the TARS project, from the spring of 2022 to the spring of 2023. Selected company specifics are presented in Table 3.3.

*Table 3.3 Participating company descriptions.*

| | Bishop | Wall-E | C-3PO |
|---|---|---|---|
| Product | Supply chain solutions for C-parts, including manufacturing, purchasing, quality control, and logistics | Lighting solutions for indoor and outdoor public environments. | Develops and manufactures gas turbines, steam turbines, and other equipment for energy generation and transmission |
| Employees (Sweden) | 1300 | 580 | 2600 |

All three companies are considered large enterprises, meaning that their internal organisation is naturally divided into specialised departments with separate management. All three companies also operate globally; however, this study focused on the organisations in Sweden. At the start of data collection, all three companies had limited experience with AI applications integrated into their existing business processes. However, they were actively exploring its potential and continuously initiating new AI-related projects.

The TARS project built on a previous pilot initiative that helped the companies identify business cases suitable for AI integration using predictive modelling. The company teams met iteratively at kick-offs, gates, and workshops to discuss their progress in developing their predictive models alongside the research team. The research project as a whole and the respective company projects followed the CRISP-DM process, dividing the work into workshops and gates aligned with its stages. CRISP-DM (Cross-Industry Standard Process for Data Mining) is a widely used process model for structuring data mining and analytics projects. It organises the work into six iterative stages: business understanding, data understanding, data preparation, modelling, evaluation, and deployment, allowing teams to move back and forth between stages in iterations (Chapman et al., 2000).

### *3.5.2. Observations' data collection*

In constructivist grounded theory, early data collection may involve ethnographic approaches that allow researchers to observe actions and

interactions in their natural settings without imposing predefined analytical categories (Charmaz, 2005). Accordingly, the initial data collection in this research consisted of observations of meetings within the TARS project. These meetings provided opportunities to follow how the individual companies worked on their respective AI projects through project members' accounts of their activities. At the same time, they offered insights into how socio-technical problem-understanding unfolded within the broader TARS project, as project teams shared experiences, learned from one another, and engaged with perspectives and input from the researchers. Importantly, the observations were limited to project meetings and did not capture company activities occurring between them. In other words, the observations captured how the company projects and related activities were presented and discussed within the TARS project meetings, rather than providing direct access to the companies' project activities between meetings.

The observation method used in this research was qualitative, unstructured, and semi-retrospective, drawing on ethnographic inquiry, as the project members were studied in a "natural habitat" (Creswell & Creswell, 2018), in line with the proposed inquiry of constructivist grounded theory (Charmaz, 2005). In practice, this meant observing the companies' AI projects by participating in live meetings, watching recordings of meetings, and, while minimising my own presence, focusing in an unstructured manner on the activities observed. According to Denscombe (2014), this type of observation is useful for collecting extensive data on complex social phenomena.

The observations were conducted between spring 2022 and the end of spring 2023, during which the TARS-project held 5 meetings of different types, as specified in Table 3.4. Project meetings were either hybrid or fully online and were recorded with audio and video using the recording function in MS Teams, where the meetings were held. The data collection consisted of live or retrospective observations of meetings, as well as repeated review of the PowerPoint slides accompanying the meetings, provided by the companies, to fully understand what was happening. I did not actively participate in any of the meetings.

*Table 3.4. Observed meetings.*

| Type of meeting | Duration | Data collection practices |
|---|---|---|
| Kick-off | 1 day | Retrospective: watching meetings, reading PPTs from companies |
| Project gate 1 | ½ day | Live observation of meetings, reading PPTs from companies |
| Project gate 2 | ½ day | Live observation of meetings, reading PPTs from companies |
| Workshop 1 | 2 days | Retrospective watching meetings, reading PPTs from companies |
| Workshop 2 | 2 days | Retrospect watching meetings, reading PPTs from companies |

It is important to note that additional companies participated in the TARS project, and that some parts of the meetings focused solely on the technical aspects of predictive modelling. As these two aspects were outside the scope of this research, meeting segments focused solely on

companies not studied or on modelling work were only listened to and noted rather than transcribed in full. A total of 16 project members from the three companies were part of the TARS project's kick-off, specified in Appendix C. This number varied over the course of the project, meaning not all project members attended every meeting; however, the attending members accounted for the work of those who did not attend. All transcribed material was inserted into the qualitative analysis software NVivo.

### *3.5.3. Observation data analysis*

The analysis began with familiarisation with the empirical material through two complementary approaches. First, recorded meetings were revisited, with notes taken and the participating companies' PowerPoint presentations consulted for additional context. Second, the transcribed material was imported into NVivo, enabling a full review of the data before systematic coding began. Figure 3.2 illustrates the analysis process.

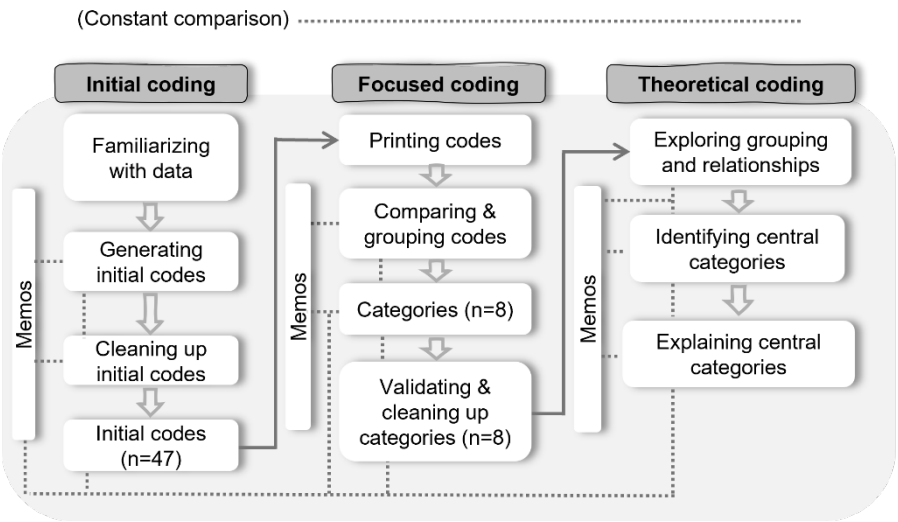


*Figure 3.2. Analysis process for observations*

Following Charmaz's (2014) constructivist grounded theory analysis procedure, initial coding involved close engagement with the material through line-by-line or incident-by-incident analysis to identify and label project teams' actions, interactions and their consequences. Codes were treated as provisional analytical interpretations, with openness to refinement as the analysis developed (Charmaz, 2014, 2017). This step of coding was conducted in NVivo and involved assigning short, descriptive codes to everything in the dataset relevant to the study's objectives. This step was conducted iteratively to validate the identified codes, as the initial codes were “cleaned up” by compiling similar concepts or removing irrelevant ones, ultimately resulting in 47 initial codes.

The next step in the analysis involved focused coding, in which initial codes were compared and organised into broader analytical categories (Charmaz, 2014). To provide a clearer overview and, thus, openness to alternative interpretations, this step was conducted manually by printing the initial codes, cutting them into individual paper strips, and physically comparing and grouping them by similarity and relationship. The process was guided by questions such as: What is happening here? How are these concepts connected? How do they relate to the research questions? This resulted in eight preliminary categories, which were subsequently reviewed against the complete dataset to assess their empirical grounding, internal coherence, and distinctiveness, and were then established (Charmaz, 2014).

The final analytical step involved theoretical coding, in which the analysis moved beyond identifying categories to exploring their relationships at a higher level of abstraction (Charmaz, 2014). Continuing with a manual approach, the focus shifted from identifying what was happening to understanding how and why the categories were related within the broader process. Through this analysis, three central categories were identified as particularly significant in explaining the phenomenon.

The final step of the Phase I analysis moved beyond the central categories to develop a more abstract explanation of their meanings and relationships. The categories were revisited in light of the research's conceptual foundations, treating them as sensitising concepts

(Charmaz, 2014). This process yielded analytical finding I, which offered a preliminary explanation of the phenomenon, partially addressed the research questions, and identified aspects requiring further exploration.

## 3.6. Phase II: Interviews

The interview study was undertaken to further investigate and explain issues that could not be fully addressed through observations alone, thereby extending understanding of how socio-technical problem-understanding unfolded in practice and what shaped its development.

### *3.6.1. Interviewed project members*

Eight project members were interviewed. From each company, two project members were purposively selected: one with expertise in data science and analysis, hereafter referred to as the data person, and one with domain-specific expertise in the organisational problem and related business processes, hereafter referred to as the business person. However, in one of the teams, the data person left the project, prompting a business person to develop data science skills to advance the project. Two university researchers were also interviewed, providing broader perspectives informed by their involvement in multiple cases. All project members had first-hand experience of the projects and could reflect on their activities and development.

### 3.6.2. Interview data collection

Semi-structured interviews were selected to explore project members' experiences of how socio-technical problem-understanding unfolded during AI integration projects and what shaped its development. Interviews enable in-depth exploration of project members' experiences and interpretations of organisational processes (Denscombe, 2014; Creswell & Creswell, 2018). The semi-structured format provided consistency across interviews while allowing flexibility to follow up on emerging insights (Säfsten & Gustavsson, 2020). This was particularly relevant, as the interviews aimed to deepen insights into the results from Phase I. The details of the interviews are provided in Table 3.5.

*Table 3.5. Interviewed project members*

| Project role | Company | Duration | Forum |
|---|---|---|---|
| Business person | Bishop | 45 min | MS Teams |
| Data person | Bishop | 34 min | MS Teams |
| Business person | Wall-E | 46 min | MS Teams |
| Data person | Wall-E | 45 min | MS Teams |
| Business person | C-3PO | 50 min | MS Teams |
| Data/business person | C-3PO | 50 min | MS Teams |
| Researcher | University | 45 min | MS Teams |
| Researcher | University | 48 min | In person |

Project members were invited to participate individually, and all interviews were conducted via MS Teams, except for one held in

person. An interview guide (Appendix D) focused on project members' experiences of the projects, particularly how organisational problems were initially understood, how this understanding developed, what influenced the process, and what lessons project members drew from their experiences working with problem-understanding. Open-ended questions encouraged reflection, while follow-up questions clarified responses and explored relevant issues in greater depth. The interviews were conducted in Autumn 2024. Each interview lasted approximately 45 minutes and was video- and audio-recorded with project members' consent. All recordings were manually transcribed to ensure familiarity with the data.

### *3.6.3. Interview data analysis*

The interview analysis, visualised in Figure 3.3, followed the same constructivist grounded theory procedures as the analysis of the observations, involving initial, focused, and theoretical coding (Charmaz, 2014). As illustrated in Figure 3.3, initial coding began with familiarisation with the interview material and the generation of initial codes, which were then reviewed and refined through constant comparison, yielding 55 codes.

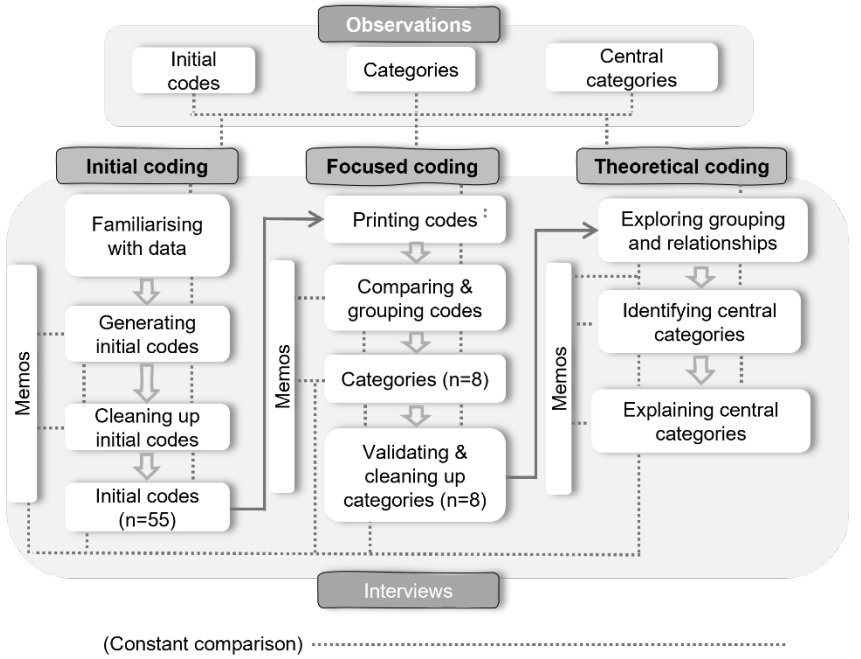


*Figure 3.3. Analysis process of interview data*

During focused coding, the initial codes were printed, manually compared, and grouped into eight categories. The subsequent theoretical coding explored relationships among these categories and developed them into three central categories (Charmaz, 2014). Throughout this process, emerging interview codes and categories were continuously compared with those developed in Phase I, allowing earlier interpretations to be revisited, challenged, and refined. The three central categories were thus developed primarily from the interview material but informed by analytical insights from Phase I.

The final step of the Phase II analysis involved revisiting these central categories in relation to the conceptual foundations, which again served as sensitising concepts (Charmaz, 2014). This supported the development of analytical finding II, which extended the findings from Phase I and provided a deeper explanation of how socio-technical problem-understanding unfolded in practice and what shaped its development.

## 3.7. Phase III: Theoretical integration

Phase III focused on integrating the two analytical findings from Phases I and II, examining their relationships to develop theoretical explanations that could address the research questions in depth. During this phase, the conceptual foundations of the thesis were revisited and brought into closer dialogue with the analytical findings to clarify their relationship and to understand them at a higher level of abstraction. This process supported the development of three theoretical findings and their associated models, which were grounded in the empirical analysis and informed by constructivist grounded theory approaches (Charmaz, 2014).

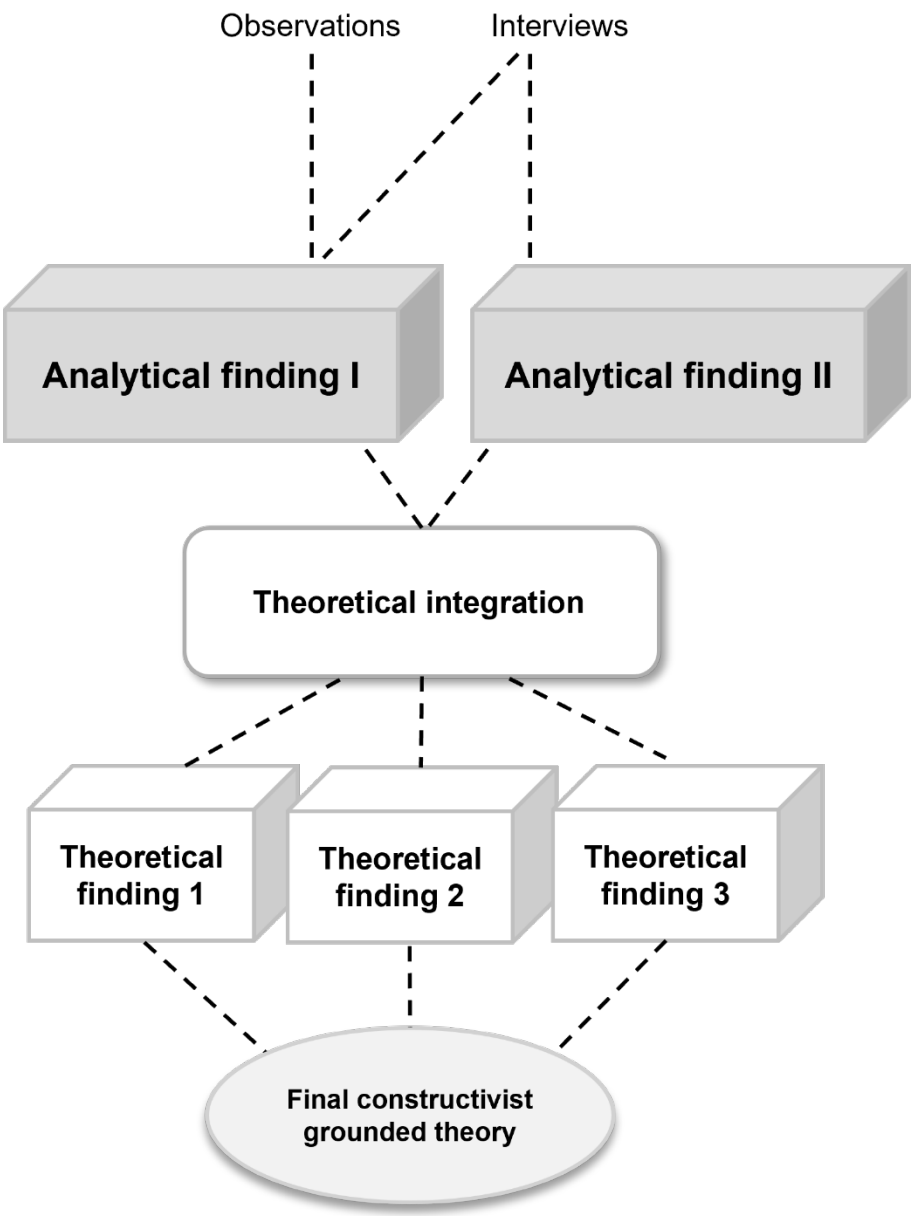


*Figure 3.4 Overview of analytical process*

Finally, the theoretical findings were situated within previous research, and, through this process, a constructivist grounded theory emerged as a theoretical contribution. Figure 3.4 illustrates this analytical progression from the two data collections to the final constructivist grounded theory. Although presented sequentially, the process was iterative, as elaborated in this chapter.

## 3.8. Research Quality and Ethical Considerations

Research quality in qualitative research can be assessed using criteria such as credibility, transferability, and transparency (Lincoln & Guba, 1985; Creswell & Creswell, 2018). Given the constructivist grounded theory approach adopted in this thesis, particular attention was also paid to Charmaz's (2014) criteria of originality, resonance, and usefulness, which address the findings' empirical grounding, theoretical contribution, relevance, and practical significance.

Credibility and transparency were supported through systematic coding, constant comparison, and memo-writing, following constructivist grounded theory procedures (Charmaz, 2014). These practices helped ensure that interpretations remained grounded in the empirical material and that analytical decisions were documented. Combining observations and interviews allowed the findings to be examined from different perspectives, while involving three manufacturing companies enabled comparisons across organisational settings, although it is recognised that their participation in an

overarching research process affected the situation. Transparency was further supported by presenting the coding process, quotes, codes and categories at different levels, and memos to show how the theoretical explanations were developed (Creswell & Creswell, 2018).

Reflexivity and researcher influence were considered throughout the research process. Qualitative research recognises that researchers' backgrounds, experiences, and involvement shape data collection and interpretation (Creswell & Creswell, 2018). Similarly, constructivist grounded theory acknowledges that theoretical explanations are constructed through researcher engagement with empirical material (Charmaz, 2008; 2014). In this study, involvement in the broader research project provided valuable contextual understanding but may also have influenced analytical focus and interpretation. For example, the emerging interest in socio-technical problem-understanding informed the subsequent interview study. Researcher influence was therefore acknowledged and addressed (see Table 3.2) through ongoing reflection and transparency, rather than treated as something to be eliminated.

Transferability in qualitative research concerns the extent to which findings may be relevant and applicable in other contexts, with detailed descriptions of the research setting and procedures enabling readers to assess this relevance (Lincoln & Guba, 1985; Creswell & Creswell, 2018). In this study, transferability must be considered in light of the specific empirical context, which involved three manufacturing

companies participating in the same collaborative AI project focused on predictive modelling. Furthermore, observations were limited to project meetings, and interviews relied on project members' retrospective accounts. These conditions constrain the extent to which the findings can be applied to other settings. However, as Lincoln and Guba (1985) emphasise, qualitative research does not aim for statistical generalisation but instead provides contextualised insights that may be transferable to other settings. Accordingly, this thesis develops theoretically grounded explanations that may inform understanding of socio-technical problem-understanding beyond the studied cases, while leaving the assessment of their applicability to other contexts to the reader.

Ethical considerations included informed participation, confidentiality, data protection, and the responsible representation of empirical material (Creswell & Creswell, 2018; Swedish Research Council, 2017). Given the relatively small number of project members and their identifiable organisational roles, particular attention was paid to protecting the confidentiality of individuals and participating organisations. Participation was voluntary and based on informed consent, and research material was handled securely in accordance with the General Data Protection Regulation (GDPR). The analysis and reporting also adhered to principles of good research practice, including careful consideration of how participants' experiences and organisational information were represented (Swedish Research Council, 2017).

## 3.9. Use of generative AI in the research process

The EU AI Act (Regulation (EU) 2024/1689) includes exemptions for scientific research and generally allows the use of AI tools in academic research, provided that applicable regulations and university guidelines are followed (European Parliament & Council of the European Union, 2024). In accordance with Jönköping University's guidance on responsible AI use, generative AI was used for the following purposes:

Generative AI was used throughout the research process as a supportive tool for reflection, learning, and academic writing. It was primarily used to discuss ideas, deepen understanding of theoretical concepts and literature, and assist with academic writing. During literature review activities, it was also used to explore relevant search terms, compare conceptual perspectives, and clarify relationships between concepts. In line with Jönköping University's guidance on responsible AI use, AI-generated information and suggestions were treated critically and evaluated against relevant academic sources (Jönköping University Library, 2026a, 2026b).

Generative AI was also used as a writing aid in preparing the thesis, including proofreading, improving clarity of language, refining formulations, and exploring alternative ways to express ideas. Consistent with Jönköping University's guidance on academic writing, AI was used to support and improve how the text presents my ideas, rather than replace my own thinking (Jönköping University Library, 2026c).

As a researcher, I take full responsibility for the content of the thesis and for the use of generative AI. All the work with the empirical material, substantive analytical decisions, interpretations, coding activities, category development, theoretical integration, and conclusions remained my own work and were grounded in the empirical material and the constructivist grounded theory analysis process.

# 4. Phase I: Observation results and the construction of analytical finding I

*This chapter presents the results from Phase I of the studies. It includes all levels of the empirical findings, the analytical construction processes up to the three central categories of Phase I, resulting in analytical finding I.*

## 4.1. What was observed

The TARS project was organised around the stages of the CRISP-DM framework, with workshops and project gates aligned with each stage, and where, as mentioned, the observations focused mainly on the first stages: business understanding and data understanding.

The meetings were conducted via MS Teams, while the workshops were held in a hybrid format. All meetings were audio- and video-recorded, providing a complete record of the discussions. The meetings were facilitated by the research team, and prior to each session, the participating companies were assigned tasks related to the current CRISP-DM phase, such as defining the problem (business-understanding phase), objectives, and success criteria before translating them into technical achievements, or identifying available data (data-understanding phase), assessing data quality, and examining how the data related to the selected organisational problem. During the meetings, each company project team presented their progress, actions, and lessons learned via PowerPoint, after which the other companies

and researchers provided feedback, asked questions, and engaged in broader discussions about the challenges encountered during the work.

## 4.2. Observed patterns of socio-technical problem-understanding

The observation study yielded eight first-level categories: *(1) Equating data-understanding with business-understanding, (2) Emergent direction, (3) Moving forward with evolving understanding, (4) Technical experimentation focus, (5) Data-driven case selection, (6) Strong focus on data work, (7) Seeking objectivity through predictive models,* and *(8) Specialised project roles*. Each category is presented below with illustrative initial codes, the memo(s) that informed its development, and is finalised with tables containing a selection of direct quotes from project meetings, serving as empirical support.

### *4.2.1. Category 1: Equating data-understanding with business-understanding*

Although CRISP-DM distinguishes between business understanding and data understanding as its first two phases, project teams frequently discussed these phases together, as if they were one and the same. When presenting and describing their cases, they mainly referred to the available data, its quality and accessibility, what it represented, and how it could be used in predictive modelling. This pattern was captured in the initial codes *Understanding of problem is data based*, *Focus on data-understanding over business-understanding*, *When project is*

*chosen, discussions focus mainly on data*, and *Displaying issues understanding how data can be used*.

Although the meetings were supposed to focus on business understanding, the teams' descriptions of their organisational problems were often framed in terms of available data and potential prediction tasks. Discussions centred on which data could be accessed, whether it was suitable for modelling, and what predictions could be produced. Questions about the organisational use of the prediction, the intended users, and the relationship between the model and the original organisational problem appeared less frequently in the observed meetings.

*Table 4.1. Empirical support for Equating data-understanding with business-understanding*

| |
|---|
| *"…its quite an interesting task to be a part of and understanding the basic data is the key"* |
| *"in the first iteration here, we describe on a high level what data is available and how this would feed the system"* |
| *"so we will talk a lot about data, we will talk about the model and then we will go on to the business case that we feel that we are going to use"* |
| *"you answered that, by saying what you want to predict using what, you don't answer it by saying how the prediction is supposed to be used. So, you go directly to the data here. You don't formulate how are we going to use it, to say, what are we going to do. And I think this is a common thing that I have seen in the presentations so far."* |

*”we did it on a high level, and to see what data we do have to use to make it possible, how can we use this data in the right ways so to say?”*

*“we met in a conference room with cakes, and did the introduction to data-driven AI but also proceeded quite directly into choosing and designing a pilot project. After that, we did quite a lot of common understanding of data understanding and preparation”*

### 4.2.2. Category 2: Emergent direction

The second category, *Emergent direction*, captures how the direction of the projects developed through the ongoing work. Rather than being fully formulated at the outset, business and technical goals became more specific through discussions, exploration, and activities within the individual case projects. The initial codes *Discussing project idea with others* and *Having trouble explaining what we want* reflected how teams developed and articulated their project ideas through interaction with researchers and colleagues with data expertise. When discussing the early identification and selection of cases, the company teams presented preliminary ideas and remained open to suggestions that could help specify the intended direction, goals, and possible contribution of AI.

Another aspect of *Emergent direction* concerned how the suitability of AI for the selected cases was explored during the projects. The initial code *Discussions whether the process actually needs AI* captured

recurring discussions about whether predictive modelling was appropriate for the process or whether other forms of digitalisation might be more suitable. These discussions contributed to the developing project direction by helping the teams clarify the technological possibilities in relation to the selected organisational case.

The category *Emergent direction* also included the initial codes *Purpose with project is to learn about machine learning* and *Wanting to understand the uniqueness of industry problems*. These codes reflected broader learning-oriented aims alongside the individual case goals. The researchers and company teams explored characteristics of manufacturing problems and the role that different AI models might play, while the company teams also sought to learn how predictive modelling projects could be approached from organisational and technical perspectives.

*Table 4.2. Empirical support for Emergent direction*

| |
|---|
| *"we realized when we had a few discussions that we have a hard time explaining exactly what we wanted"* |
| "*that is one of the reasons – we did not specify enough, and yeah its comes back to the root we say…we did not get because we did not specify enough what we wanted out"* |
| *"so we have not showed the results before because we did not think it was necessary, because we had to go back one step and see and.. give specification of what we need"* |
| *"If you go from a manual process, then and you want to sort of improve that with automated decision making, you have to think very carefully about whether this* |

*indeed just a matter of having this process digitized or to use computers to do this process. It might be that its just regular IT, its simple rules, its calculations that you know how to perform, and just getting that into the system will provide the adequate support for this task".*

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*"so, it's also to learn about how to set up a machine learning algorithm and how to work with data, the data we have, to see if that's doable or not. So that's another reason for us doing this"*

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*"knowing how little we know, like ok, its like opening up new area – how to communicate it, how to visualize it, how to educate back home so to say. What kind of people do we talk to Monday morning, you know that kind of thing…how we communicate".*

### 4.2.3. Category 3: Moving forward with evolving understanding

When company teams and researchers reflected on the success factors and challenges of their projects during the meetings, they repeatedly emphasised that the initial phase, that is, focusing on problem and business understanding outside of data collection and the final predictive model, is crucial for developing effective systems that can be implemented in the end. At the same time, project teams repeatedly reflected on the importance of this phase while describing how project activities continued alongside an evolving understanding of the problem, leading to the code *Moving forward with evolving understanding*.

The importance factor is most evident in the code *Acknowledge importance of understanding problem social and technical*, where project teams discussed the challenges faced during the project and, in particular, highlighted that they should devote more time and energy to understanding their chosen problems.

In extension, the importance of the initial phases was acknowledged in direct connection to the actual implementation phase, or the "deployment" phase in accordance with the CRISP-DM process. This was visible in the codes *A finished system does not equal a solved business problem* and *Acknowledge that problem-understanding and implementation are closely connected*, where project teams discussed how the use of the finished system, its organisational application, and its relationship to the business case remained topics of discussion alongside ongoing data and modelling work.

Although the initial phase of an AI integration project was acknowledged as important, the project teams did not indicate that it received much attention in their meeting descriptions. This is reflected in the code *Team accepts not understanding all aspects of the problem*, which captures how project teams proceeded with project activities while different aspects of the organisational problem remained to be further explored.

*Table 4.3. Empirical support for Moving forward with evolving understanding*

| |
|---|
| *"we need to focus much more on the business case and sort of understanding the use case"* |
| *"having a prediction without a business case"* |
| *"and I mean you saw the results, we don't think we can really apply it, as for now you know it is not an actual business case"* |
| *"we have some questions as well, reflections. Who in the organisation is going to use the tool?"* |
| *"when I read that* (that we need a solid case to develop an applicable prediction) *it's easy to read that and just nod and say, "yes this makes sense" but it misses such a crucial step in the design of setting up the task"* |
| *"…they produce an official forecast for a particular month looking forward … and exactly how they do this is not very clear to us"* |
| *"we do some kind of forecast, and we don't really know how this process works"* |

### 4.2.4. Category 4: Technical experimentation focus

The category *Technical experimentation focus* captures how project discussions and activities frequently centred on modelling work, prediction tasks, and the development of predictive models. This pattern was visible both in how project teams described their work and in the activities discussed during meetings. It was reflected in the codes *Solving prediction problem over solving business problem* and *Eager to discuss and start with prediction model*, which captured recurring references to model development, prediction performance, and technical aspects of the projects.

For example, during the meetings reflecting on the process as a whole, several team members highlighted their excitement at having successfully made a technical prediction. In addition, when the project

teams were asked to describe their entire process, they either said they focused on the modelling work or rushed through the business understanding to get to the modelling.

*Table 4.4. Empirical support for Technical experimentation focus*

| |
|---|
| *"it was most interesting to see that could build a model, and with different data and to get a result"* |
| *"I mean we have a really really really good prediction or at least good enough for our use case"* |
| *"we focused pretty much our time on making the model and also to include conformal regression into the model, so that was our focus basically"* |
| *"we spent a lot of time here* (CRISP-DM phases data-understanding, data preparation, modelling) |
| *"and we started to create the model quite early"* |

### 4.2.5. Category 5: Data-driven case selection

According to the empirical material, how the project teams chose their specific cases was partly dependent on the overarching research project's objectives and partly on internal factors and external pressures. However, the selection was generally based on technical aspects, such as what data was available, what form of prediction work was possible, and what could be technically achieved within the frames of the project. These notions were central to generating the category *"Data-driven case selection".* The empirical material showed that the project cases were partly selected based on the potential value AI could

create, but more so on available data and the instructions provided within the project.

The included codes *Case chosen based on data* and *Display pressure to use the data we have* further capture that the data was a driving force in choosing the project. The teams explained that when identifying potential cases for this project, the amount, quality and accessibility of data were among the main factors. Another aspect was an underlying pressure to use the organisations' data, as if company data were assigned a value that needed to be extracted.

Moreover, as the studied research project followed the procedures in the CRISP-DM framework and was time-restricted, the project teams were highly impacted by both the frameworks' and the researchers' methodology when choosing the project, visible in the codes *Researchers and CRISP-DM requirements shape start of project,* and *Choosing simpler pilot project to suit demands*. An additional, and recurring aspect in terms of choosing the project based on technological conditions, was that the nature of the organisational problem was a main decision factor. This was visible in the codes *Discussing business process impact on problem,* and *Case chosen based on task or process,* showing how the project teams discussed their chosen cases, focusing primarily on specific sub-processes and activities rather than broader organisational aspects.

*Table 4.5. Empirical support for Data-driven case selection*

| |
|---|
| *"the task* (from the researchers based on CRISP-DM) *was to identify a use case where data analysis could provide some kind of value to the company and where we could see that there was data available"* |
| *"we learned that the data we have today we sadly cannot use".* |
| *"I still think that this is anyway an opportunity to use the data that we have"* |
| *"we looked into the data we had, and there was a lot of data, but we also found that all the data was not saved so there was not enough historical data to use".* |
| *"and see if we could predict that* (the chosen case)*, what data we had and how we could use it, so that was when we talked a lot together we found out that this is what we can find out and maybe get some results"* |

### 4.2.6. Category 6: Strong focus on data work

When discussing and describing their work, project teams focused on data from several perspectives. This was seen in the code *Discussions are mainly about data*, meaning that most of the discussions during the meetings (regardless of the CRISP-DM phase it was meant to be about), were about data availability, data management, data quality and possibilities with that said data.

Project teams discussed the importance of ensuring alignment between business needs and available data when selecting data for the project, seen in the code *Discussing that business and data aspects must match.* Subsequently, the amount, quality and accessibility of data was often discussed as a challenge in the companies' respective project cases, visible in the codes *Production volume affects data amount, Discussion on external factor impact on data, Recognising system impact on data, Discussing human involvement impact on data, Issues in accessing*

*data,* and *Data amount and quality important.* Aside from the nature and retrieval of data, discussions also revolved around how to handle the data once it is gathered, visible in the codes *Explaining data preparation, Anomalies in data removed* and *Use of data discussed with researchers and team.*

*Table 4.6. Empirical support for Strong focus on data work*

| |
|---|
| *"what we did then was to really think about, together with the research group, what the instances* (data) *should be and the input and the output"* |
| *"we did some sort of cleaning up, so still, we had to address some data quality issues",* |
| *"there has been quite a lot of data crunching actually"* |
| *"we knew for sure that it was not gathered in one place* (data) *and we have to take data from different places"* |
| *"I mean there are a number of people that are manually adding in some data here, and to be honest, some of them are not very good at it so that is of course a challenge"* |
| *"it's very difficult for us what it's going to be* (the results of the chosen case process), *and right now we don't actually have that data"* |
| *"good data is a very very good key to have good results. And perhaps more sources"* |
| *"the main problem was, as ever, to identify a suitable problem and to ensure that data is available"* |
| *"some of the projects we deemed unsuitable as it was unclear how to set them up as a predictive problem; either there was not one target attribute or there was no historic data to train the model on"* |

### 4.2.7. Category 7: Seeking objectivity through predictive models

Unlike the uncertainty surrounding project goals and direction, project teams frequently described predictive modelling as a means of supporting organisational decision-making through more data-driven assessments. This notion is captured in the category *"Seeking objectivity through predictive models",* where the codes *Describing current process as manual, Describing current forecasts and human analysis, Discussing that current process is money-driven* and *Acknowledge cultural impact on current process* represents the pattern that the project teams chose their cases for a potential AI implementation, as they currently view the case processes as flawed due to human factors.

The code *Purpose of predictive model is objective decision support* captured project teams' descriptions of predictive models as a source of numerical support for organisational decisions. When describing existing processes, project teams referred to manual forecasting, incomplete information, financial considerations, and human judgement. They discussed using model outputs alongside existing decision-making to provide an additional basis for forecasts and other assessments.

*Table 4.7. Empirical support for Seeking objectivity through predictive models*

| |
|---|
| *"its still a risk to do it right now* (over-scheduling production), *but we will have something that backs that decision* (if predictive model is implemented as decision support). |
| *"When it comes to the manual forecasting in excel it was not as easy, I would say, the data quality is not that good. You can see that there are figures missing, there are weeks missing where the forecast has not been produced, so it was quite a challenge to get some good information from that. I think that's what you get when you have a completely manual process"* |
| *"their* (the functions currently doing the forecasting) *goal and target is from a money perspective, not from a unit perspective"* |
| *"we don't know exactly how that goes* (forecasts in the current process) *but we know that the official forecast might have some political touch to it, what we can do of course is to see afterwards how good the official forecast was compared to what actually came out of it"* |

### 4.2.8. Category 8: Specialised project roles

The category *Specialised project roles* included the code *Small teams*. Across the cases, the project teams generally consisted of a *data person* and one or two *business persons*. In one company, the team also included a middle manager without direct responsibility for digitalisation. In another company, the data person left during the project, and one of the business persons began learning data analysis to continue the project work.

The code *Function-based division of work* captured how tasks and discussions were divided between team members. Business persons

primarily discussed the organisational case, while data people primarily discussed data, modelling, and other technical activities. The code *Project reliant on data person* captured recurring references to the data person's role in accessing, preparing, and modelling data. The code *Project kept kind of secret* captured that, in two companies, the specific case project had not been discussed with other functions or departments connected to the selected process.

*Table 4.8. Empirical support for Specialised project roles*

| |
|---|
| *"they* (other functions/department) *do not even know we are doing this, so we are starting in our own corner so to say to see what comes out of it, and after that we will probably have, or we will have a discussion with them"* |
| *and we are trying to learn the self-studies and we will also take in turn on wards so to say, to play with these tools"* |
| *"and a concern we have, X* (data person) *has been with us up until now, but X will leave the company, so it's very much about how to use the time X has left, and as you understand we are very reliant on having a data analyst in this project"* |
| *"I mean, we would like to take this model and make some use case for it, also from the process perspective and the user friendliness, it should be something that more or less not only X* (their data person) *can do"* |
| *"and then our data analyst started to create a model"* |
| *"and X* (data person) *did a good job extracting data in a good format … so X did a lot of the data preparation for us, so to speak"* |

## 4.3. What Phase I revealed about socio-technical problem-understanding

As illustrated in Figure 4.1, the first-level categories were synthesised from related empirical patterns and grouped into the central categories of *Technical narrowing, Navigating unclear goals,* and *Expertise dependencies.*

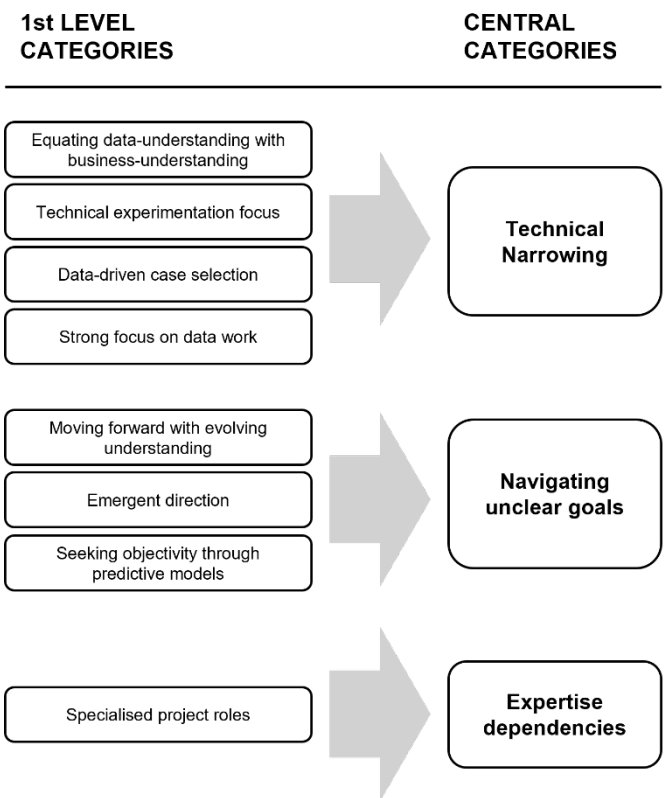


*Figure 4.1. Category structure of Phase I.*

### 4.3.1. Technical narrowing

The first central category, *Technical narrowing*, was developed from four first-level categories: *Equating data-understanding with business-understanding, Technical experimentation focus, Data-driven case selection,* and *Strong focus on data work.* These categories were grouped together because they captured different but related ways in which the teams' activities increasingly centred on data, the problem as a prediction task, modelling, and technical possibilities.

The first-level categories reflected this pattern across the projects. Data availability and the feasibility of formulating prediction tasks based on that data were considered during case selection, while discussions of the organisational problems frequently centred on data-related questions. As the projects progressed, considerable attention was directed towards data preparation, modelling, and technical experimentation. These activities provided concrete tasks and results around which the teams continued their work. Technical narrowing, therefore, captures how socio-technical problem-understanding became increasingly oriented towards what could be examined using available data and predictive models. This does not imply that organisational concerns disappeared, but rather that technical activities became increasingly prominent in how problem-understanding unfolded.

### 4.3.2. Navigating unclear goals

The second central category, *Navigating unclear goals*, was developed from *Emergent direction*, *Moving forward with evolving understanding*, and *Seeking objectivity through predictive models*. These categories were grouped because they showed that project teams continued to progress on their projects while socio-technical problem-understanding remained emergent.

The teams struggled to articulate clear goals and to define the underlying purposes of their predictions. Nevertheless, they continued to develop prediction tasks and explore technical possibilities despite unresolved questions about organisational needs, prospective users, and intended use. A recurring aspiration was to support more objective decision-making, though this was not always translated into specific project objectives. Together, these patterns formed the central category Navigating unclear goals, capturing how teams continued to act and make decisions while their understanding of what the projects should achieve remained incomplete and evolving.

### 4.3.3. Expertise dependencies

The third central category, *Expertise dependencies*, was developed from the first-level category *Specialised project roles*. Although based primarily on a single first-level category, theoretical coding highlighted its broader analytical significance for understanding how expertise shaped the teams' actions. Here, it is important to note that analytical

memos also raised questions about who possessed the expertise to articulate project goals, explain organisational needs, and relate them to technical possibilities.

The observations showed that relevant expertise was distributed among project members with different responsibilities and areas of expertise. The distinction between business persons and data persons was particularly prominent, reflecting differences in organisational, process-related, and technical expertise. While the teams brought together these forms of expertise, their contributions to the ongoing work varied, and certain activities depended on individuals with specialised expertise in data preparation, analysis, and modelling. Participation from actors beyond the immediate project teams was also limited. *Expertise dependencies* therefore simply captured how teams relied on specialised expertise from different organisational functions in problem-understanding.

### *4.3.4. Finding I: A drift towards technical feasibility*

The continued analysis focused on the relationships among Navigating unclear goals, Expertise dependencies, and Technical narrowing. Consistent with constructivist grounded theory, this analytical step involved moving beyond the individual categories and engaging with the conceptual foundations as sensitising concepts (Charmaz, 2014, 2017), thereby providing points of departure for examining and developing the emerging findings.

Pragmatist and socio-technical perspectives directed attention to understanding as an ongoing process of inquiry and to the relationships between the social and technical aspects of organisational problems (Dewey, 1938; Morgan, 2020; Davis et al., 2014). In the observed projects, teams began with identified organisational needs, but their understanding of these needs was emerging. At the same time, they started with technology, and the expertise was distributed among specialised actors. As teams continued working with unclear goals and distributed expertise, increasingly centred on data and individuals' technical work, while organisational aspects of the problems received less attention, this showed a technical narrowing. Consequently, the focus of problem-understanding shifted towards what could be achieved with available data and predictive modelling.

Together, the three central categories capture how socio-technical problem-understanding unfolded as an ongoing process that gradually drifted towards technical feasibility. This formed the basis for the first analytical finding, *A drift towards technical feasibility*, as illustrated in Figure 4.2.

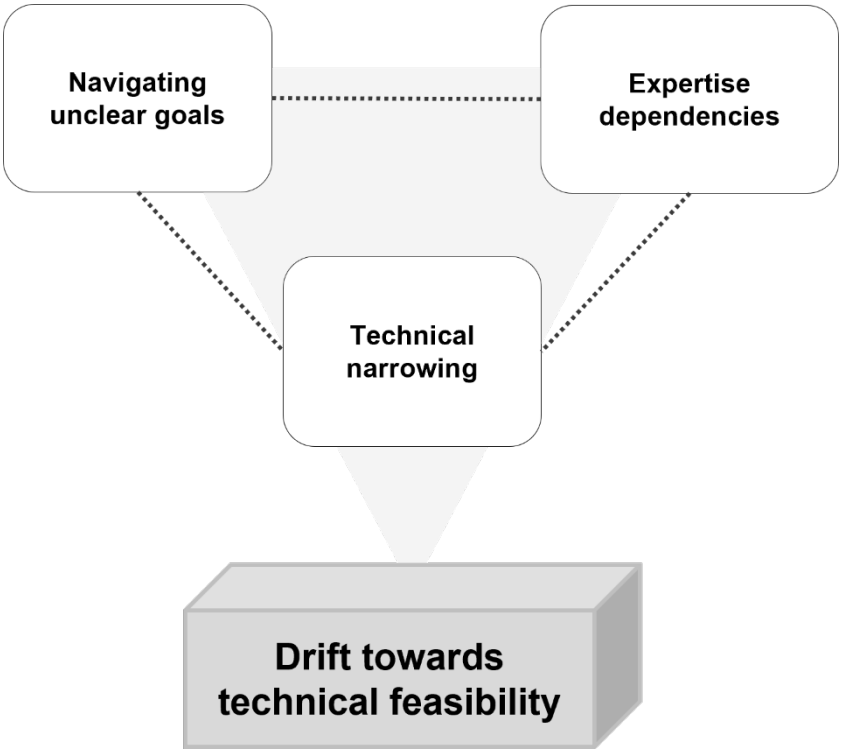


*Figure 4.2. Analytical finding I: Drift towards technical feasibility*

However, this drift did not represent a deliberate abandonment of organisational needs in the projects. Rather, it describes a gradual shift in the practical basis through which the teams explored, formulated, and developed their understanding of their problems.

Although Phase I identified a drift towards technical feasibility, the findings only partially address how socio-technical problem-understanding unfolded in practice and what shaped its development. In particular, the observations could not fully explain how project teams developed direction despite emerging understanding of the problem,

how different forms of expertise contributed to this work, or why technical activities became increasingly influential in shaping subsequent inquiry. These unresolved questions therefore guided the analytical focus of Phase II, allowing the emerging explanation from Phase I to be further explored and developed through project members' experiences and reflections.

# 5. Phase II: Interview results and the development of analytical finding II

*Chapter 5 outlines the results of Phase II, including interview findings, the central categories of this phase, and the construction and content of analytical finding II.*

## 5.1. Interviews extending the explanation of socio-technical problem-understanding

Phase II builds on the unanswered questions from Phase I by exploring project members' experiences and reflections on how socio-technical problem-understanding unfolded across the projects and what shaped its development, extending the emerging explanation.

## 5.2. Project members' experiences of socio-technical problem-understanding

The interview study yielded eight first-level categories based on project members' reflections on their experiences of socio-technical problem-understanding during the AI integration projects. The categories are: *(1) Tension between speed and maturity,* (2) *Recognising distributed expertise*, *(3) People as drivers for collective momentum*, *(4) Time and structure as enabling conditions, (5) Challenges in integrating expertise (6) Tension between understanding and experimenting, (7) Need for making the problem explicit, and (8) Emerging data awareness.* Each category is presented below with illustrative initial

codes and selected interview excerpts that support and exemplify the findings.

### *5.2.1. Category 1: Tension between speed and maturity*

Throughout the interviews, project teams described pressures to maintain pace and demonstrate progress, alongside the need to repeatedly revisit and refine their understanding of the organisational problem, the available data, and the intended AI application. Project teams often expressed an eagerness to begin experimenting with data and AI models, sometimes moving quickly through the initial stages of the CRISP-DM process, particularly business understanding. This was reflected in the initial codes *"Eagerness to start with AI model"*, *"Newness of AI makes project hard to structure"*, *"AI is fun to experiment with"*, and *"Rushing because of hype of AI"*.

Several team members explained that they initially believed their understanding of the organisational problem was sufficient to proceed with technical work, but subsequently discovered uncertainties that required them to revisit earlier assumptions and return to business-understanding activities. Team members also emphasised that technical experimentation was necessary for learning about the problem, rather than something that should be postponed until a complete understanding had been established. However, they described how moving too quickly into modelling could result in misunderstandings and subsequent rework. These experiences were reflected in the initial codes *"AI needs to go fast but also take time"*, *"Important not to rush*

*process"*, *"You need to experiment with AI to learn"*, and *"Need for experimentation and keep centred on problem"*.

*Table 5.1. Empirical support for Tension between speed and maturity*

| |
|---|
| *"…and we came through the first phases much faster since we did not have to jump that much back and forth, we learned from the initial iterations".* |
| *"we probably jumped too fast between iterations, and then we had to work our way back… to make it more effective you have to make sure to do the work in the beginning".* |
| *"If you would have done it correctly from the beginning, you would have maybe researched it more, but I don't know if that would have made any difference, you would have probably just gone for it anyways. I mean we were so eager to get a model up quickly, test it and see what we get… I mean that's what you want in the end right?* |

### 5.2.2. Category 2: Recognising distributed expertise

Project members described challenges in obtaining relevant competence and emphasised that these extended beyond individual project members to the organisation more broadly. This was reflected in the initial codes *"Challenges in getting the right competence and knowledge"*, *"It is an organisational question of competence"*, and *"It is more about people and competence than business understanding"*.

Project members particularly highlighted gaps in data science competence, reflected in *"Business persons lack sufficient data science*

*knowledge"*, *"The fire souls do not have the right competence and skills"*, *"General need for more data science competence"*, and *"Knowledge and competence on how to use data needed"*. At the same time, they emphasised the importance of practical knowledge of organisational processes, reflected in *"Tacit knowledge of process important"*.

Across the interviews, project members described a need to integrate process knowledge, data knowledge, and AI competence, as reflected in *"Cross-functional knowledge or person needed for success"*. They suggested that this could involve individuals, roles, or organisational arrangements capable of bringing different forms of expertise together. Notably, project members more often discussed the need for business persons to develop data and AI competence than for data persons to develop deeper process knowledge. They also described expertise integration as an organisational concern, involving the broader ability to access, develop, and connect relevant competence beyond the immediate project team.

*Table 5.2. Empirical support for Recognising distributed expertise*

| |
|---|
| *"That competence (data science/analytics) needs to be there, someone who knows what data is available, what data can be generated, how you can extract the data and where it is, so all the parts"* |
| *"You should have someone appointed with data analysis as a central competence and have that as their area of expertise"* |
| *"Its not enough to have an "process-person" and a "data-person", you need someone who focuses in between"* |

*"We could use a competence that is in the middle, who does not only work with logistics or only work with IT, but more dedicated to work with the IT-based logistics systems"*

*"We knew we had the data we needed to put in, but we did not really know how to use it, and there we needed help"*

### 5.2.3. Category 3: People as drivers for collective momentum

This category captures how project team members described the importance of broader involvement and sustained momentum throughout the AI projects, emphasising that involving more people early could spread knowledge, reduce dependence on individuals, bring additional perspectives to understanding problems, and support the eventual integration of AI into organisational practice. This was reflected in the initial codes *"Important to be included in project early"* and *"Involving more people important"*.

At the same time, project members repeatedly emphasised the importance of maintaining momentum in the projects. This was reflected in the initial codes *"There is a need for passion"* and *"Joined team based on interest"*. Here, they described how progress often depended on individuals willing to invest time, energy, and interest in moving the work forward. In several cases, a dedicated "data person" played a particularly important role, as reflected in the initial codes *"Data person needed for many tasks"* and *"Data scientist leading project equalled best results"*. While such individuals were considered

important for project progress, project members also recognised the risks of becoming overly dependent on a small number of actors in case of organisational changes.

*Table 5.3. Empirical support for People as drivers for collective momentum*

| |
|---|
| *"we had to give up a bit, and did not have the energy to start over (a reason why project did not continue)"* |
| *"perhaps there was no will to put in the needed capacity"* |
| *"as long as there is people that thinks this (AI) is exciting and that we learn, we will go forward"* |
| *"…and one thing we would have done differently is to maybe have had a bit more people, not necessarily in the main part of the project but at least in the background"* |
| *"When you only work with a few people, it gets kind of sensitive… a relatively small part of the organisation was involved in this from the beginning"* |
| *"For us, we maybe should have involved more people and explained it to more people during the project"* |

### 5.2.4. Category 4: Time and structure as enabling conditions

This category captures how project members described time, resources, and structure as enabling conditions during the work. They frequently reported that developing customised AI solutions required more time and resources than anticipated, and that there is a need for external

resources and structure when working with AI integration, reflected in the initial codes *"Important to make AI project a main focus and not something on the side"*, *"Need for time and resources to perform project properly"*, *"Potential with project but not launched, mostly due to time"*, *"Took more time than expected"*, and *"Building your own takes resources"*.

Project members explained that AI projects were often carried out alongside routine work responsibilities, limiting opportunities to sustain progress, involve additional actors, and revisit assumptions about organisational problems. Several cited insufficient time and resources as reasons projects lost momentum or failed to progress beyond the pilot stage.

Project members also emphasised the importance of structure for coordinating the work, reflected in the initial codes *"Need for structure in AI projects, both before and during"*, *"CRISP-DM good as boundary communication object"*, and *"CRISP-DM good for beginners"*. Although the projects already followed CRISP-DM, the project members particularly valued the framework for providing a shared structure and common reference points. They described how its phases helped business persons and data people communicate, coordinate activities, and maintain an overview of project progress, particularly when established organisational routines for AI integration were limited.

*Table 5.4. Empirical support for Time and structure as enabling conditions*

| |
|---|
| *"when you are in a team with different competences and roles, it can be obvious, well it is obvious for the one doing it, but maybe its not that obvious for everyone, and then to be clear with, where are we now? (in the CRISP-DM process)"* |
| *"If you want it (the AI project output) to work, you kind of have to work in accordance with this model"* |
| *"it's (AI) new to so many people, and then you maybe get a little more curious than you are in your usual job where you are used to… or where there is directives and policies for how to, you know, stay within the frames"* |
| *"we don't have the resources, basically, to be too many from our organisation in the projects, we don't have that much extra time"* |
| *"… that someone has this as a side thing, it makes it (the AI project) more sensitive for disruptions in the organisation"* |
| *"we have never worked coordinated with this (AI)… but its been more like "yeah, we can do this, let's go!" and then that kind of infects on an organisational level, like this is the way to do it"* |
| *"Quite often it was pretty challenging in terms of, you know, it's like a side project to our actual work. So it was not easy for us to actually prioritise the project over our actual jobs".* |

### 5.2.5. Category 5: Challenges in integrating expertise

This category captures how project members described collaboration between different areas of expertise and the challenges of integrating these contributions into a shared understanding of organisational problems. Although business persons and data persons generally

collaborated well, their expertise often remained separated according to specialised roles rather than being fully integrated in the ongoing work. Project members described communication challenges across these roles and disruptions when key individuals left or changed responsibilities, reflected in the initial codes *"Challenge in communication between data-people and business-people"* and *"Change in organisation and team affect project progress"*.

Project members emphasised that effective collaboration required more than *sharing* expertise between individuals. They highlighted the importance of developing a collective understanding of the problem and how different expertise related to one another, reflected in *"Joint understanding in team important"* and *"Project choice must be jointly understood from data and business perspective"*. Project members also valued opportunities to exchange experiences with other companies in the collaborative research project, reflected in *"Gaining a lot by sharing knowledge with other companies"*. Together, these reflections highlighted a distinction between *sharing* expertise between specialised roles and *integrating* different forms of expertise into a shared understanding in the work.

*Table 5.5. Empirical support for Challenges in integrating expertise*

| |
|---|
| *"it was also very interesting to see the other companies too, and you know, what challenges they had"* |
| *"we went to the workshops and got a bit more understanding of what we could do"* |

| |
|---|
| *"the workshops were good, then we got to exchange experiences on what others were doing"* |
| *"To kind of sync, well it has to do with business understanding as well, and using the right data from a business perspective. Its easy that it boils down to only numbers for the data person. They can be smart as hell, but they don't know everything about how it looks, what we do today or how we work"* |
| *"I take that with me, that I got insight into it (the data based work), and it gave me so much to build on, just like understanding the tools used, which needs to be used and what is the difference between them"* |
| *"It (the AI project) can't only be hung up on person"* |
| *"the final months we lost our data person completely, and then when we did that, it kind of went limb – like how we do this now? How do we take on the project now?... if we would have started over, we would have made sure to have more people"* |
| *"there was not enough instructions from the one who quit, a bit unfortunately* |
| *"the data people are really good at what they are doing, but they speak a whole different language"* |

### 5.2.6. Category 6: Tension between understanding and experimenting

This category captures how project members described the need to develop a sufficient understanding of the organisational problem before proceeding with technical work, while recognising that further understanding could only emerge through experimentation. Project members emphasised the importance of allocating time to early problem/business-understanding activities and repeatedly revisiting them throughout the projects. This was reflected in the initial codes

*"Important to make time for initial phases"*, *"Need for iteration back to first phase several times"*, and *"The more focus in the beginning, the less iterations later"*.

At the same time, project members explained that working with data and AI models revealed previously unidentified questions, assumptions, and relationships, reflected in *"Problem- and data understanding can only be understood after test"*. Technical experimentation was therefore described as necessary not only for developing solutions but also for further understanding the organisational problem. They also highlighted the importance of considering organisational needs, intended use, and implementation early in the projects, reflected in *"Integration plan needed from the beginning"*, *"Important to base AI project on real problem"*, *"End use important to understand from the beginning"*, and *"Good business-understanding does not equal good problem-understanding"*. Together, these reflections illustrate how project members sought to establish a sufficient basis for technical development while recognising that socio-technical problem-understanding needed to be continuously revisited and refined through experimentation.

*Table 5.6. Empirical support for Tension between understanding and experimenting*

| |
|---|
| *"Its not enough to find a good case, we need to find a case or a process where the information (given by the AI) actually fits and where you can draw benefit from it in a real decision-making situation",* and *"we learned a lot about how to work with data towards business case"* |

| |
|---|
| *"so we went back rapidly and then… well simply started re-engineer, and I know that we looked more closely at the numbers and: what do we really need?"* |
| *"we came out with a model, and saw the results from it, and then we could conclude that we had to change our in data and then that model turned out good, I think"* |
| *"we really had to go back and start over.. how does it work today… many had their perception of how it worked, I did not have full knowledge on how it worked either, so we realized that we need to go back and get the same picture"* |

### 5.2.7. Category 7: Need for making the problem explicit

This category captures project members' reflections on the need to make the problem and what they are currently working on more explicit throughout the projects. They described how use cases, assumptions, and emergent understandings often remained informal and were not systematically documented or revisited. This was reflected in the initial codes *"Use case was more of a discussion than a task"*, *"No clear use case"*, and *"Cannot answer how problem-understanding was documented"*. As a result, project members found it difficult to trace how their understanding of the organisational problem had developed over time and what they learned about it during the process.

Project members emphasised the value of clearly formulating and documenting the problem, reflected in *"Clear use case needed"*, *"Problem-understanding needs to be written down to be obvious"*, and

*"No documentation of project brings challenges"*. They explained that making assumptions, decisions, and emergent understandings explicit could support communication, allow earlier decisions to be revisited, and improve continuity if/when project members changed. This was further reflected in *"A well-defined use case can be used as a communicative bridge"* and *"Transferring knowledge challenging"*. Overall, project members viewed explicit problem formulation and documentation as ways to support a shared and continuously developing understanding of the organisational problem.

*Table 5.7. Empirical support for Need for making the problem explicit*

| |
|---|
| *"I don't remember really… we probably sat together and thought about it…"* |
| *"I came up with the suggestion, and there were not that many other suggestions… so we were more like "yeah, but thesis could be a first good case".* |
| *"and there was not much more analysis to that actually (use case formulation)".* |
| *"we did some changes a long the way there too, I think, based on that we knew what we would have, and we needed more data"* |
| *"finally you have to write it down, what is it that we want, get it on paper and see… is this what we want now? Are we with this or have we missed something? So you have to speak up in some way and get it on paper, actual words that says "we want to blab la bla…", and it is then when it all becomes obvious"* |
| *"those who eere there knows what we did and got, what data we used, how we got it, to try doing that from the beginning with new people (when the team changed) we did not have it documented enough"* |

*"it's very hard to get a knowledge transfer from someone who has done this a small portion of their job to a new person coming in and learning a new context"*

### 5.2.8. Category 8: Emerging data awareness

This category captures how project members' understanding of data developed throughout the projects alongside their understanding of the organisational problem. Although data was a prominent topic in the interviews, reflected in the initial code *"Talk mostly about data when asked about problem-understanding"*, project members primarily discussed how their perceptions of relevant and necessary data changed as the work progressed.

Project members described initially assuming they knew which data was needed, but discovering additional requirements and limitations through technical experimentation. This was reflected in *"Knowing what data is important is important"* and *"Learned what data needed to be saved"*. They also reported difficulties assessing data quality, quantity, and suitability beforehand, reflected in *"How much data that is much is relative"* and *"Data quality hard to decide in beforehand"*. Working with data revealed missing information, quality issues, and previously overlooked possibilities.

Project members further described how emergent understanding of the problem helped them identify relevant data, while exploring the data revealed new aspects of the problem. Their reflections therefore showed

how data-understanding and business-understanding (as CRISP-DM stages) developed together, with insights from each informing the other throughout the projects.

*Table 5.8. Empirical support for Emerging data awareness*

| |
|---|
| *"we had the data, but we did not save it, and that was stupid because we could have gained so much more from this project, but that was a learning point"* |
| *"the data we had was then useless all of a sudden, and you realize that data is pretty valuable"* |
| *"we are not even able to do a simple report with this data, so we will definitely not have enough data points to, you know, do any AI"* |
| *"suddenly it all looked crazy… and then we had it explained to us that this data, its too inconsistent so there is no way to make an analysis out of it"* |
| *"its when you gather all the data to the same level and you see that it is relatively little"* |

## 5.3. What Phase II further revealed about socio-technical problem-understanding

Building on the questions that remained after Phase I, the eight first-level categories were grouped into three central categories: *Temporary anchors for progress*, *Sharing distributed expertise*, and *Experimenting as problem-understanding*. As illustrated in Figure 5.1, these categories extend the three central categories developed in Phase I, providing a more detailed explanation of how socio-technical problem-understanding unfolded and what shaped its development.

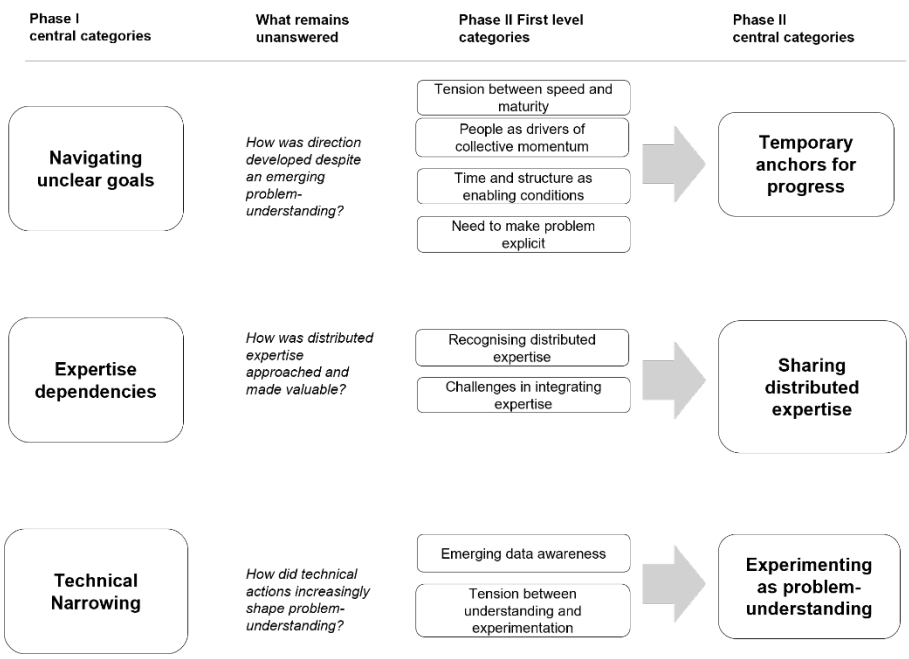


*Figure 5.1. Development of central categories through Phase I and Phase II.*

### *5.3.1. Temporary anchors for progress*

The first central category, *Temporary anchors for progress*, was developed from four first-level categories: *Tension between speed and maturity*, *Time and structure as enabling conditions*, *Need for making the problem explicit*, and *People as drivers of collective momentum*. These categories were grouped together because they captured different perspectives of the need and use for temporary anchors; concrete elements in the projects that allowed for the teams to base their actions and make progress.

Across these categories, project members referred to different ways of establishing direction and maintaining progress, including using shared project structures to coordinate activities and relying on committed individuals to sustain the work. They also described the need to balance continued progress with opportunities to revisit and develop their understanding in terms of time and structure, and emphasised the importance of making problems, assumptions, and intended applications more explicit, although these were not consistently documented or revisited during the projects.

These patterns extended *Navigating unclear goals* from Phase I by providing further insight into how project teams continued working during emerging problem-understanding. While the observations showed that teams navigated unclear goals, the interviews described the different reference points that project members used to coordinate activities, make decisions, and shape what to pursue next. Some of these were already part of the ongoing work, while others were identified retrospectively as practices that could have supported the projects. Together, these patterns formed the central category *Temporary anchors for progress*, capturing how project members used, or recognised the need for, temporary points of reference to support continued action while problem-understanding emerged.

### *5.3.2. Sharing distributed expertise*

The second central category, *Sharing distributed expertise*, was derived from two first-level categories: *Recognising distributed expertise* and

*Challenges in integrating expertise*. These categories were grouped because they present two complementary perspectives on expertise, simply summarised as teams sharing expertise rather than integrating it.

Project members described how different forms of expertise were brought into the projects. They generally reported positive collaboration and opportunities to exchange expertise, but also described difficulties in communicating across specialised roles, accessing relevant competence, and maintaining continuity when key individuals were unavailable or left the projects. While different forms of expertise were shared during the work, project members also emphasised the need to develop a more shared understanding of the organisational problems and how the different contributions related to one another.

These patterns extended the *Expertise dependencies* from Phase I by providing further insight into how project members experienced and worked with distributed expertise. While the observations identified reliance on specialised actors, the interviews described how expertise was exchanged and coordinated, and how it was sometimes difficult to bring together in ongoing work. Together, these patterns formed the central category *Sharing distributed expertise*, capturing how project members exchanged and coordinated specialised expertise during the projects, while the integration of these contributions remained a challenge.

### 5.3.3. *Experimenting as problem-understanding*

The third central category, *Experimenting as problem-understanding*, was developed from two first-level categories: *Emerging data awareness* and *Tension between understanding and experimentation*. These categories were grouped because they showed how working with data and AI models yielded new insights into the data, prompting project members to revisit earlier assumptions and reconsider what they were trying to achieve. At the same time, their developing understanding of the problems informed what data they examined and how they approached further experimentation.

In these categories, project members reported discovering previously unrecognised data requirements, limitations, and possibilities as technical work progressed. These experiences led them to reconsider which data was relevant, what predictions could be developed, and how these related to the organisational problems. Project members also described returning to earlier assumptions and revisiting business-understanding activities when experimentation raised new questions. At the same time, they emphasised the importance of having a sufficient initial understanding of the problem to guide technical work, while recognising that this understanding continued to develop through experimentation.

These patterns extended *Technical narrowing* from Phase I by providing further insight into the role of technical experimentation in problem-understanding. While the observations showed that project

activities became increasingly focused on data and modelling, the interviews described how working with data and AI models also contributed to the development of the teams' emerging problem-understanding. Together, these patterns formed the central category *Experimenting as problem-understanding*, capturing how problem-understanding emerged through ongoing technical experimentation.

### *5.3.4. Analytical finding II: A process of emergence and provisional understandings*

Project members described how working with data and predictive models revealed new information about the organisational problems, prompting them to revisit earlier assumptions and reconsider their objectives. This demonstrates *experimenting as problem-understanding,* grounded in the pragmatist view of understanding as something that develops through ongoing inquiry, in which actions and their consequences inform subsequent understanding and action (Dewey, 1938; Morgan, 2020). At the same time, *temporary anchors* provided reference points around which continued action could be based. These understandings, in turn, guided subsequent activities and could be reconsidered as new information emerged, showing the recursive relationship between experimenting and temporary anchors.

Perspectives on sensemaking and technological frames (Weick, 1995; Orlikowski & Gash, 1994) provided sensitising concepts for examining how *sharing distributed expertise* related to this process. In the projects, expertise was distributed, and project members described difficulties in

integrating these contributions. Sharing distributed expertise was therefore connected to the recursive relationship between experimentation and temporary anchors, as an informing factor, influencing how the recursive process unfolded by directing focus.

Together, the three central categories captured the emergence of socio-technical problem-understanding while project members continued working through temporary anchors and provisional understandings. Experimentation contributed new information that could change how the problems were understood, while temporary anchors provided points of reference for continued inquiry. Different forms of expertise informed this process, though they were shared more often than integrated. These relationships formed the basis for the second analytical finding, *A process of emergence and provisional understandings*, as illustrated in Figure 5.2.

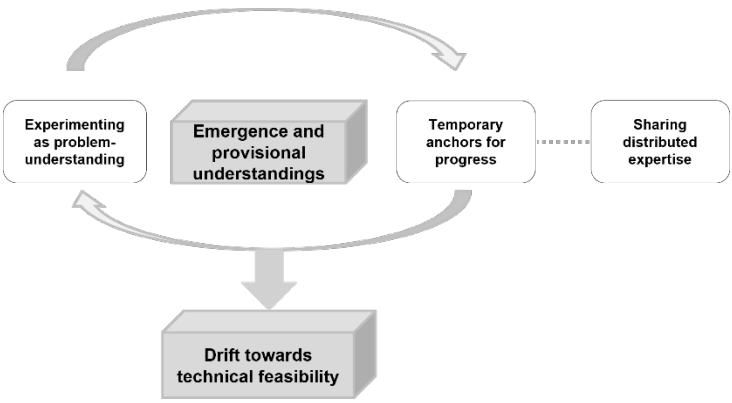


*Figure 5.2. Analytical finding II: A process of emergence and provisional understandings, and its relationship to the drift towards technical feasibility.*

This finding also provides further insight into the drift towards technical feasibility identified in Phase I. as seen in Figure 5.2. While the observations showed that problem-understanding gradually became oriented towards technical activities, the interviews described how technical experimentation contributed to the emergence of problem-understanding. As data and modelling activities continued, the temporary anchors became increasingly technical, provisional understandings that guided subsequent work, which increasingly focused on technical possibilities, while broader organisational aspects of the problems received less attention. The two analytical findings therefore show both how socio-technical problem-understanding unfolded as a process and how its direction gradually shifted towards technical feasibility.

Although Phase II provided further insight into socio-technical problem-understanding, the empirical findings did not yet fully explain how this process and its direction were related, the relationships between social and technical elements, or what shaped its development. These questions informed Phase III, in which the analytical findings were synthesised and examined in relation to the conceptual foundations to develop a theoretically integrated explanation that addresses RQ1 and RQ2.

# 6. Phase III: Theoretical integration

*This chapter presents the theoretical integration of the analytical findings from Phase I and II. By relating the findings to the conceptual foundations, this chapter answers the research questions and generates the three theoretical findings that serve as the main building blocks of the final constructivist grounded theory.*

## 6.1. Answering RQ1: Socio-technical problem-understanding unfolding as a recursive and directional process of emergence and provisional understandings

The two findings, *Drift towards technical feasibility* and *A process of emergence and provisional understandings*, provide complementary insights into how socio-technical problem-understanding unfolded in the AI integration projects studied. While the first identified how problem-understanding became increasingly oriented towards technology, the second explained how understanding developed in this direction through experimentation, temporary anchors that created provisional understandings, and shared expertise.

First, the findings depart from stage-based approaches to problem-solving in terms of distinguishing problem identification and definition from subsequent solution development (D'Zurilla & Goldfried, 1971; Basadur et al., 1982). Rather than following a clearly separated sequence, the findings demonstrate that problem-understanding continued to develop throughout the projects, alongside

experimentation and solution development. At the same time, the findings align with cognitive approaches that emphasise how problem representations guide subsequent search and action (Newell & Simon, 1972; Simon & Hayes, 1976; Simon, 1973; Mumford et al., 1994). While these perspectives acknowledge that problem representations can be revised and guide subsequent action, the findings provide further insight into how this relationship unfolds over time. Specifically, they show how provisional understandings emerge through ongoing inquiry anchored in temporary anchors and, in turn, direct what is investigated next. This can be understood in relation to sensemaking research, which emphasises how selected cues are used to construct plausible understandings that enable action under conditions of uncertainty (Weick, 1995; Weick et al., 2005). Importantly, this recursive process was not directionally neutral, as successive provisional understandings cumulatively directed problem-understanding towards the problem's technical aspects.

The emergent character of this process aligns with pragmatist inquiry (Dewey, 1938; Morgan, 2020) and with research on problem framing, innovation, and complex problem-solving, which suggests that problem-understanding often develops through exploration, reframing, and engagement with uncertain situations (Schön, 1983; Dorst, 2011; Frensch & Funke, 1995; Koen et al., 2001; Magistretti et al., 2025; von Hippel & von Krogh, 2016). It also aligns with Dewey's (1938) distinction between a problematic situation and a problem that develops through inquiry, and the idea that problem formulation and solution

development can be intertwined rather than separate activities (Schön, 1983; von Hippel & von Krogh, 2016).

Experimentation contributed not only to evaluating potential solutions but also to developing problem-understanding. At the same time, its continued emergence did not necessarily result in a more socio-technically comprehensive understanding of the organisational problem. Instead, the technical narrowing that evolved through this experimentation increasingly shaped the provisional understandings that guided subsequent inquiry, suggesting that socio-technical problem-understanding unfolded not only as an emergent process but also as a directional one, in which each new inquiry influenced the next focus. Because technical experimentation produced concrete tasks, observable results, and relatively immediate feedback, it provided readily available temporary anchors for continued action. As these anchors increasingly shaped provisional understandings, subsequent inquiry became progressively oriented towards technical feasibility.

### *6.1.1. Theoretical finding I: The SPEP model*

This first theoretical integration is synthesised in the SPEP model (***S****ocio-technical* ***P****roblem-understanding through* ***E****mergence and* ***P****rovisional understandings*)**,** presented in Figure 6.1. The model conceptualises socio-technical problem-understanding as a continuing, recursive and directional process in which ongoing inquiry generates new insights, temporary anchors provide a basis for provisional understandings, and these understandings guide subsequent inquiry.

The two intertwined trajectories in the figure represent *technical experimentation* and *organisational inquiry*, illustrating how understanding develops through interconnected but analytically distinguishable actions. Technical experimentation refers to activities that explore data, model possibilities, and assess technical feasibility, while organisational inquiry refers to activities to understand organisational needs, specific work practices, the social parts of data, and intended use.

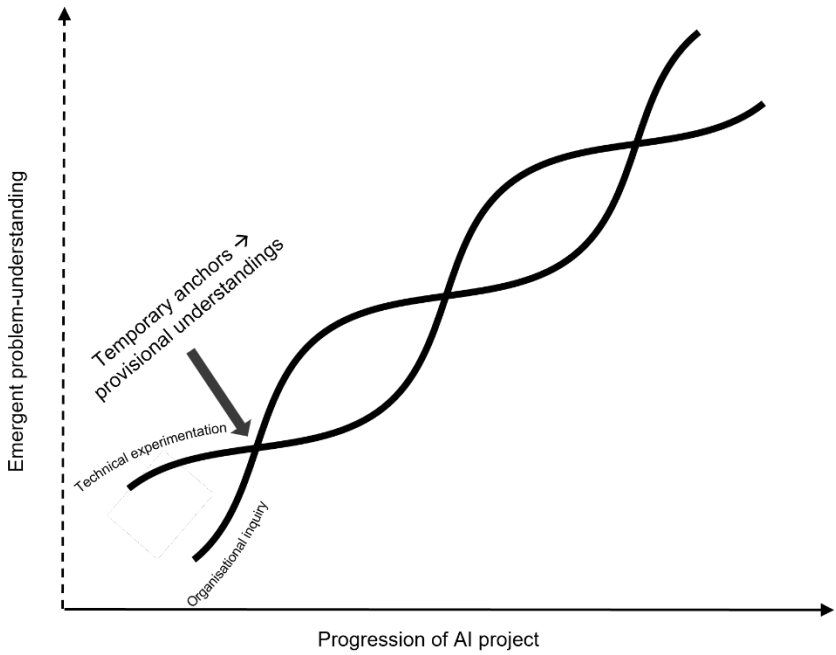


*Figure 6.1. SPEP model: Socio-technical problem-understanding in AI integration projects as a recursive and directional process of emergence and provisional understandings*

Their recurring intersections represent points where temporary anchors provide a basis for developing *provisional understandings*, where the arrow illustrates how these understandings guide subsequent action. Depending on the nature of the temporary anchors and the provisional understandings, the process is not only recursive but also directional. When temporary anchors are primarily technical, the resulting provisional understandings may similarly emphasise technical aspects of the problem, thereby orienting subsequent inquiry in that direction. Over successive iterations, this can cumulatively shape the trajectory of socio-technical problem-understanding.

Importantly, SPEP does not suggest that technical experimentation and organisational inquiry necessarily emerge equally or remain continuously integrated, nor does it show that the emerging process amounts to a more comprehensive socio-technical problem-understanding over time. For example, technical experimentation may deepen understanding of what can be predicted without correspondingly developing an understanding of how these predictions relate to organisational needs. The horizontal axis represents the progression of the AI integration project, while the vertical axis represents the emergence of problem-understanding. Together, they illustrate how understanding emerges as project activities unfold, without implying that project progression necessarily produces a more comprehensive understanding. Rather, the direction of understanding

depends on the actions taken, the nature of the temporary anchors, and the provisional understandings that guide continued inquiry.

The distinction between technical experimentation and organisational inquiry is particularly relevant in relation to predictive AI integration. While prediction-oriented cognitive insight represents an important application of AI (Davenport & Ronanki, 2018), understanding what can be predicted is not necessarily the same as understanding how predictions relate to organisational problems or support decision-making. This distinction resonates with discussions of AI solutionism, where technological possibilities risk taking precedence over organisational problems (Adobor, 2026). The uncertainty associated with AI technologies (Berente et al., 2021) also makes experimentation important for exploring technical possibilities. However, as illustrated by SPEP, the outcomes of such experimentation may become temporary anchors, shaping provisional understandings and directing subsequent inquiry that are mainly technical.

SPEP answers RQ1: *How does socio-technical problem-understanding unfold in practice in AI integration projects?* By explaining that problem-understanding in AI integration unfolds through a recursive, directional process of emergence and provisional understandings. As AI integration project teams engage in technical experimentation and organisational inquiry, new insights emerge, informing provisional understandings that guide subsequent action. Because these understandings shape what is investigated next, the process is also

directional and can become cumulative: what receives attention in the provisional framings strongly influences a project's development. The model thereby explains not only how problem-understanding continues to emerge throughout AI integration projects, but also how the nature of temporary anchors and provisional understandings can progressively reinforce particular interpretations of the organisational problem.

SPEP addresses RQ1 by integrating the two analytical findings to explain how socio-technical problem-understanding unfolded through a recursive, directional process of experimentation, temporary anchors, and provisional understandings. However, the theoretical integration also involved examining the relationships between the analytical categories to explain what shaped this process, as addressed by RQ2. In particular, *Sharing distributed expertise* highlighted that understanding organisational problems involved interconnected socio-technical aspects, but that sharing expertise about these aspects did not necessarily result in an integrated understanding of their relationships. Similarly, *Temporary anchors for progress*, *Tension between speed and maturity*, and *Time and structure as enabling conditions* highlighted how project arrangements influenced opportunities to develop and revisit understandings.

## 6.2. Answering RQ2: Socio-technical problem-understanding as relationally constituted and shaped by organising conditions

To further understand the socio-technical elements involved in AI integration problem-understanding and their relationships, the empirical material was examined in relation to technology, organisation, people, and process, drawing on socio-technical systems thinking (Leavitt, 1965; Davis et al., 2014). Particular attention was also given to data, a recurring concern in the projects and emphasised in AI integration research (Uren & Edwards, 2023). In this analysis, data was treated as part of the technological element. Table 6.1 presents the socio-technical recurring concerns identified in the empirical material, organised according to these four elements. Although grouped under individual elements, many concerns involved relationships across several elements, reflecting the interdependencies emphasised in socio-technical research (Appelbaum, 1997; Klein, 2014; Fox, 1995).

*Table 6.1. Socio-technical concerns and their interdependence*

| | Technology | Organisation | People | Process |
|---|---|---|---|---|
| Technology | • Modelling possibilities, development, performance | • Available and accessible data<br>• Data quality, consistency, and completeness<br>• Data volume and historical data<br>• How data was generated, entered, stored, managed | • How data was generated, entered, stored, managed<br>• Data preparation<br>• AI capabilities and limitations<br>• Prediction quality and outcomes<br>• Data knowledge<br>• AI competence and knowledge<br>• Ability to evaluate whether AI suited problem | • What the data represented<br>• How data was generated, entered, stored, managed<br>• Relationship of AI systems vs regular system<br>• Possibility to formulate process as prediction task<br>• Where and how data was generated in process<br>• Whether the process was suitable for AI |
| Organisation | | • Business need, purpose, goals, expected value<br>• Time and resources available<br>• Ability to integrate expertise<br>• Early and broad involvement of relevant people | • General business- & organisational knowledge<br>• Level of crossfunctional expertise | • Intended and expected use, applicability<br>• Where and how data was generated in process<br>• How intended prediction & existing process relate |
| People | | | • Individual interest and "passion" | • Level of explicit and implicit knowledge in process<br>• Knowledge of existing work in process |
| Process | | | | • How the current process worked |

However, beyond their interdependence, the relational character of these concerns was particularly evident in the way most technical aspects gained significance through organisational practices and purposes, and vice versa. For example, understanding data quality required examining how information was generated and recorded through existing work processes, while assessing the usefulness of predictive models depended on the organisational decisions and human judgement they were expected to support.

These findings are therefore closely related to both socio-technical (Leavitt, 1965; Fox, 1995; Davis et al., 2014) and sociomaterial understandings of socio-technical relationships, as they emphasise both how these elements function as analytical entry points and how social and material aspects are constitutively entangled in sociomaterial practice (Orlikowski, 2007; Orlikowski & Scott, 2008; Orlikowski, 2010). Therefore, these perspectives are treated as complementary in

understanding the findings of this research. For example, data could not be understood solely as a technical resource, since its quality, relevance, and potential usefulness depended on the work practices through which it was produced, the people interpreting it, and the organisational decisions it was intended to inform. However, data, as an "isolated" element, functioned as a suitable starting point for understanding these constitutive relationships and for practical engagement. From this perspective, socio-technical problem-understanding develops through inquiry into organisational problems, in which technological, organisational, people-related, and process-related aspects derive their meaning from their relationships with one another.

### *6.2.1. Theoretical finding II: TOPP: a constitutive relational model of socio-technical problem-understanding*

The constitutive relational understanding of the socio-technical elements of socio-technical problem-understanding is synthesised in the TOPP model (***T****echnology,* ***O****rganisation,* ***P****eople, and* ***P****rocess*), presented in Figure 6.2. The model conceptualises socio-technical problem-understanding as an inquiry into the constitutive relationships between technological, organisational, people-related, and process-related aspects of organisational problems. While the findings showed that these aspects were interconnected and that their relationships were often acknowledged, they were not necessarily explored as part of the ongoing inquiry. This suggests that socio-technical problem-understanding is shaped not only by the elements considered, but also

by the extent to which their relationships are investigated and brought into the developing understanding of the problem.

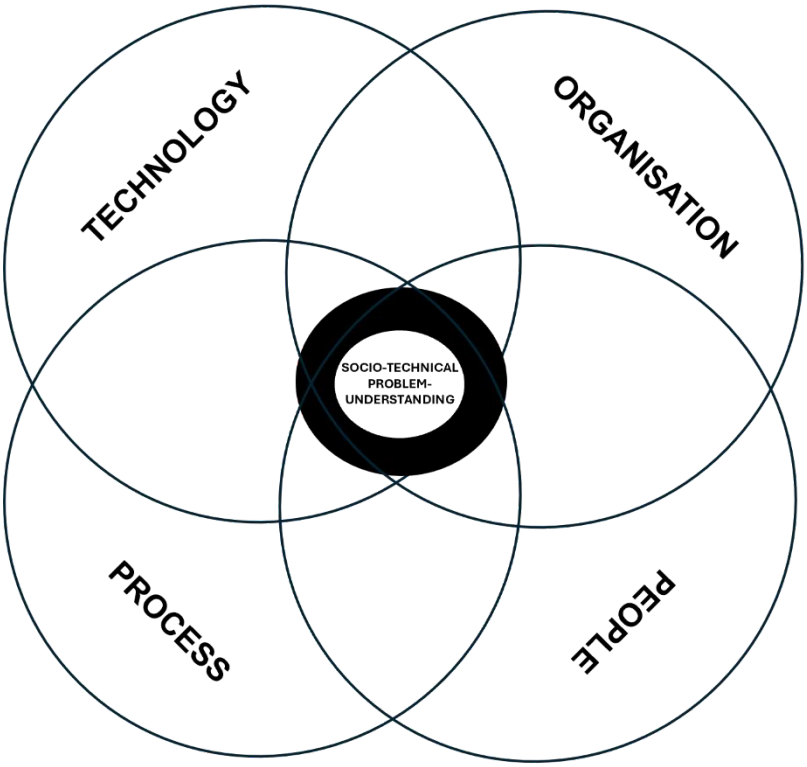


*Figure 6.2. TOPP: A constitutive relational model of socio-technical problem-understanding in practice*

The four overlapping elements represent analytically distinguishable but constitutively related (in accordance with the sociomaterial view Orlikowski, 2007; Orlikowski & Scott, 2008; Orlikowski, 2010) aspects of organisational problems in AI integration, whose meaning

and significance develop through their relationships in practice. The flower-like structure illustrates how all four socio-technical elements are mutually shaped through their constitutive relationships in practice. As these relationships cannot be fully represented in two dimensions, the positioning and overlaps of the circles carry no particular analytical significance. Rather, the figure represents the continuous entanglement of all four elements, without suggesting that any particular relationship is more central or influential than another. Whereas SPEP explains how problem-understanding unfolds through emergence and provisional understandings, TOPP explains *what* project teams sought to understand.

The TOPP model contributes to *RQ2: What shapes the development of socio-technical problem-understanding in AI integration projects?* by demonstrating that problem-understanding is shaped by the constitutive relationships between Technology, Organisation, People, and Process while they can still be approached as analytically separate in socio-technical inquiry. However, rather than influencing understanding as separate elements, their meaning and significance emerge through their relationships in practice.

### *6.2.2. Theoretical finding III: POF: Organising conditions as shaping socio-technical problem-understanding*

The analytical findings and their central categories showed that socio-technical problem-understanding was shaped not only by the socio-technical elements and their relationships, but also by how the inquiry

was organised. Across the projects, arrangements for coordinating activities, allocating resources, involving expertise, and establishing expectations of progress were also shaping conditions. This was particularly evident in the analytical category *Temporary anchors for progress*, including *Tension between speed and maturity* and Time and structure as enabling conditions, which highlighted how project arrangements provided direction for continued work while also shaping opportunities to investigate and reconsider the organisational problem.

These findings can be understood in light of research conceptualising projects as temporary forms of organising that coordinate people, resources, and activities around particular objectives (Lundin & Söderholm, 1995; Packendorff, 1995; Davies & Hobday, 2005). Such arrangements provide conditions for collective action, but in the findings, they also establish boundaries around what can be investigated.

In the AI integration projects studied, socio-technical problem-understanding was found to be emergent, and internally shaped by the constitutive relationships among technology, organisation, people, and processes. Consequently, understanding an organisational problem involved more than identifying relevant elements; it required exploring how these elements related to one another and reconsidering these relationships as new insights emerged. This meant that neither the questions requiring investigation nor the expertise and activities needed to address them could necessarily be fully determined at the outset.

At the same time, the AI integration initiatives were organised as projects, which are temporary forms of organising characterised by bounded timeframes, specific tasks, and collective action (Lundin & Söderholm, 1995; Packendorff, 1995), that provide arrangements for coordinating activities, resources, and specialised expertise (Davies & Hobday, 2005). In the projects studied, these arrangements shaped how the inquiry into organisational problems was structured and conducted: while project arrangements were established around anticipated activities, responsibilities, and outcomes, the emergent nature of socio-technical problem-understanding meant that the questions requiring investigation and the activities and expertise needed to address them were acknowledged as developing throughout the projects. This tension was reflected in the empirical findings, as project teams described a sense of urgency to progress with technical activities while retrospectively recognising that more time should have been devoted to investigating and understanding the organisational problems. These observations suggest an uncomfortable fit between established project arrangements and the emergent requirements of socio-technical inquiry. The organising conditions thus shaped the development of socio-technical problem-understanding by influencing the space in which problem-understanding could emerge. At the same time, the emergence of new questions and socio-technical relationships could necessitate a reconsideration of how the inquiry was organised, including the activities, expertise, and resources required.

The theoretical integration, synthesising recurring organising aspects and the analytical findings and the conceptual foundations, yielded four organising conditions: *Structure*, Resources, *Expertise*, and *Direction*. Together, these constitute the ***P****roject* ***O****rganising* ***F****rame* (POF), illustrated in Figure 6.3.

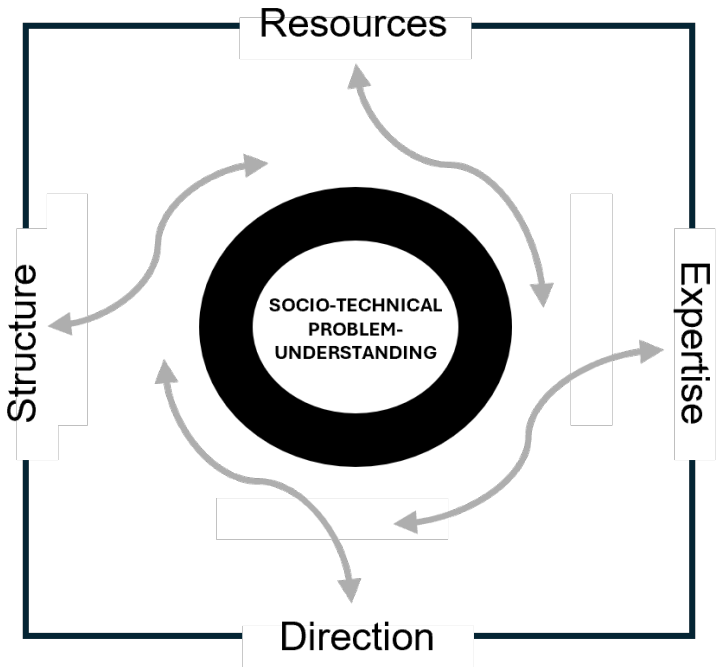


*Figure 6.3. POF: Project organising frame as a shaping condition for socio-technical problem-understanding*

*Structure* concerns how project activities and responsibilities are organised and coordinated, including the use of process models such as CRISP-DM, as well as responsibilities and ways of working. *Resources* concern the availability and allocation of time and capacity in the project. *Expertise* concerns which form of knowledge and ability to put

into practice are available, involved, and brought into the inquiry. Finally, *Direction* concerns how project objectives, expectations of progress, and anticipated deliverables influence which questions and activities are prioritised. At the centre of POF, the ongoing inquiry into socio-technical problem-understanding is illustrated. The curved arrows illustrate how organising conditions shape these activities, while emerging understandings may also reveal the need to reconsider organising. POF therefore conceptualises how project organising shapes the development and direction of socio-technical problem-understanding, while emerging understandings may, in turn, create a need to reconsider how the project is organised.

POF contributes to answering RQ2 by explaining how project organising shapes the development and direction of socio-technical problem-understanding. Specifically, it identifies Structure, Resources, Expertise, and Direction as organising conditions that shape the space in which socio-technical problem-understanding unfolds, shaping which aspects of the organisational problem are explored, and specify which forms of expertise are involved. At the same time, emerging understandings may prompt a reconsideration of these arrangements.

## 6.3. Summary of theoretical findings

The theoretical integration examined relationships among the analytical findings in Phases I and II, informed by the study's conceptual foundations. Through constant comparison, abductive reasoning, and

consulting the memos, the analysis moved beyond identifying what occurred in the projects to a more abstract level, explaining how socio-technical problem-understanding unfolded, what it concerned, and the conditions shaping its development. Three interconnected theoretical findings emerged from this process. First, the relationships among experimentation, temporary anchors, provisional understandings, and the observed drift towards technical feasibility informed the conceptualisation of socio-technical problem-understanding as an emergent, recursive, and directional process (SPEP). Second, the interdependencies among the technical, organisational, people, and process-related concerns encountered in the projects informed a constitutive relational conceptualisation, shaping the content of socio-technical problem-understanding (TOPP). Third, the observed influence of project arrangements on the space for socio-technical problem-understanding informed the conceptualisation of organising conditions that shape its development and direction (POF). Together, these theoretical findings provide complementary, empirically grounded explanations of how socio-technical problem-understanding unfolded in AI integration projects in practice and what shaped it, thereby answering RQ1 and RQ2.

# 7. Discussions

*This chapter places the theoretical findings in dialogue with previous research on AI integration and integrates them into the final constructivist grounded theory. The model is then discussed in terms of its practical implications, followed by a methodological discussion and reflections on future research. The chapter concludes.*

## 7.1. Theoretical contribution: Towards a constructivist grounded theory of socio-technical problem-understanding in AI integration

The purpose of this thesis was to explore and explain how socio-technical problem-understanding unfolds in practice and what shapes it in AI integration projects, by constructing an empirically grounded theory. In addition, the research aimed to develop a framework to provide practical guidance for organisations undertaking AI integration initiatives. Chapter 6 developed three complementary theoretical findings: SPEP, a process model of socio-technical problem-understanding; TOPP, a constitutive relational model of socio-technical problem-understanding in practice; and POF, which shows the organising conditions that shape socio-technical problem-understanding. Together, these theoretical findings explain how socio-technical problem-understanding develops, what is understood, and how its organising conditions shape its direction. Their integration forms the basis of the proposed final constructivist grounded theory.

### *7.1.1. STP-AI: An integrated model of socio-technical problem-understanding in AI integration initiatives (SPEP-TOPP-POF)*

As illustrated in Figure 7.1, the integrated SPEP–TOPP-POF model provides an explanatory model that brings together the recursive process by which problem-understanding develops, the relational socio-technical substance of what is being understood, and the organising conditions that shape the possibilities for continued inquiry.

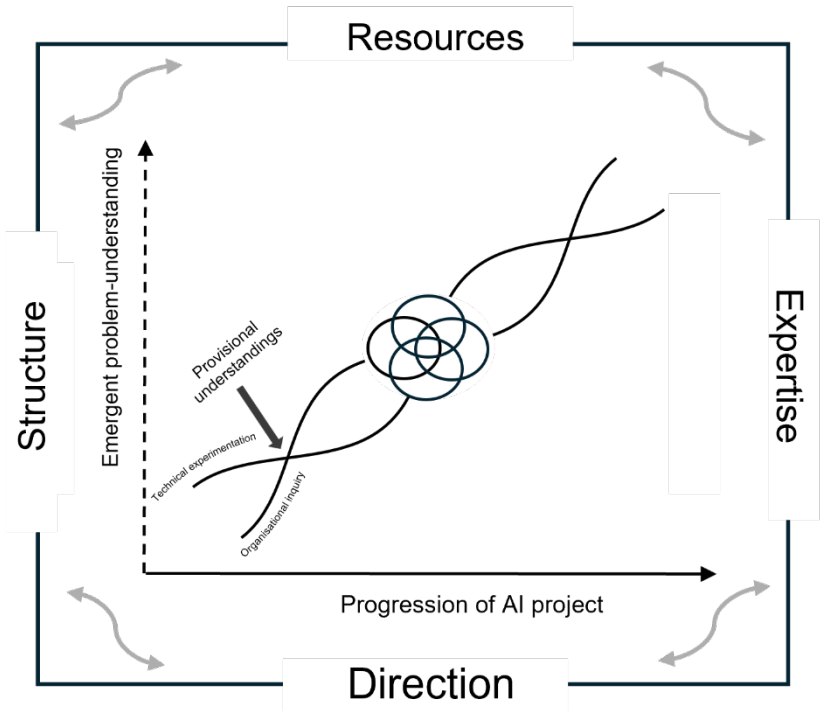


*Figure 7.1. STP-AI: An integration of SPEP, TOPP and POF in the context of AI integration: Final constructivist grounded theory of socio-technical problem-understanding in AI integration projects*

As illustrated in Figure 7.1, SPEP explains how understanding emerges through recursive interactions between technical experimentation and organisational inquiry, while TOPP represents how the socio-technical elements of that understanding are constitutively related. POF adds the organising conditions within which this inquiry unfolds and how emerging understanding can, in turn, influence suitable organising conditions. STP-AI therefore stands for ***S****PEP,* ***T****OPP,* and ***P****OF* in AI integration.

The model explains how socio-technical problem-understanding can remain emergent while gradually and cumulatively drifting in a particular direction. As project arrangements influence which activities are prioritised, they also shape opportunities to develop understanding of socio-technical relationships. For example, when progress is expected and time is limited, technical experimentation may be prioritised because its concrete, observable outcomes provide temporary anchors from which provisional understandings can develop. These understandings then guide subsequent inquiry towards further technical possibilities, reinforcing the focus on technical feasibility. Over time, this recursive process may draw attention away from broader socio-technical relationships, even though the organisational problem in AI integration consists of the constitutive relationship between socio-technical elements.

The findings of this thesis are consistent with previous research recognising that organisational problems are emergent, that problem-

understanding develops through inquiry and reframing, that AI integration involves interconnected socio-technical and organisational challenges, and that organising structures influence the possibilities of AI initiatives (Dewey, 1938; Schön, 1983; Dorst, 2011; Makarius et al., 2020; Niehaus & Wiesche, 2021; Haefner et al., 2023; Jarrahi et al., 2023). The theoretical contribution therefore lies not in identifying these characteristics individually, but in explaining how they interact in practice. The following sections discuss these theoretical contributions in relation to previous research on AI integration, highlighting how the findings support, complement, and extend existing knowledge.

### *7.1.2. From emergent to directional problem-understanding*

Previous research on innovation, problem setting, and framing recognises that organisational problems are not necessarily fully understood from the outset, but may evolve through exploration, uncertainty, and reframing (Koen et al., 2001; Reid & de Brentani, 2004; Schön, 1983; Dorst, 2011; Magistretti et al., 2025). Similarly, problem-solving research acknowledges that understandings of problems and potential solutions may develop together as new knowledge emerges (Frensch & Funke, 1995; von Hippel & von Krogh, 2016). The findings of this thesis support these perspectives by demonstrating that socio-technical problem-understanding emerges through ongoing inquiry, in which insights continuously inform and reshape understanding of organisational problems.

Furthermore, the negotiated and evolving character of data science problem formulation has already been demonstrated by Passi and Barocas (2019) and Passi and Sengers (2020). Passi and Barocas (2019) show how translating organisational objectives into analytical problems involves interpretation, negotiation, and consequential formulation decisions, while Passi and Sengers (2020) demonstrate how understandings of data science systems' purposes, functions, and evaluation evolve during development. The findings confirm this broader understanding of AI integration work as an ongoing socio-technical accomplishment. The contribution of this thesis is therefore not to establish that problem formulations influence subsequent action, but to explain how provisional understandings emerge through ongoing inquiry and progressively shape its direction. In AI integration projects, this helps explain how technical experimentation can reinforce a focus on technical feasibility, while broader socio-technical aspects of the organisational problem remain insufficiently explored.

These findings also align with Selbst et al. (2019), who demonstrate how abstraction can obscure important socio-technical relationships, and Adobor (2026), who identifies problem oversimplification and ballistic adoption as mechanisms contributing to AI solutionism. While Adobor (2026) explains how complex organisational problems may be reduced to technical AI solutions and how commitment to these solutions can be reinforced, the findings of this thesis provide a complementary explanation of how such tendencies may develop through ongoing problem-understanding, highlighting how the

recursive nature of problem-understanding can also make it directional, potentially reinforcing technical narrowing through ordinary project activities rather than through deliberate decisions to prioritise technology over organisational needs. This directional explanation is also consistent with research showing that the framing of a problem influences subsequent technological activities (Vaccaro et al., 2011). The findings of this thesis extend this in the context of AI integration, suggesting that the relationship is recursive rather than one-directional.

Drawing on pragmatist perspectives on inquiry and the consequences of action (Dewey, 1938; Morgan, 2020), the findings explain how problem-understanding can remain emergent while becoming increasingly guided by prior understandings and activities. Importantly, continued inquiry does not necessarily lead to a broader or more comprehensive understanding of the organisational problem. Instead, its directional nature further emphasises the active acknowledgement of socio-technical considerations and of how these elements are related.

### *7.1.3. From socio-technical interdependent to socio-technical constitutively related*

Previous research on AI integration and digital transformation has established that technological capabilities alone are insufficient for creating organisational value. Instead, successful integration depends on several "social" elements, such as organisational readiness, cross-functional collaboration, work practices, employee capabilities, and human expertise (Davenport & Ronanki, 2018; Fountaine et al., 2019;

Makarius et al., 2020; Niehaus & Wiesche, 2021; Jarrahi et al., 2023; Uren & Edwards, 2023; Haefner et al., 2023). This socio-technical perspective is further reflected in research emphasising human–AI complementarity (Jarrahi, 2018), the multiple organisational, technological, and human dimensions of AI implementation (Lee et al., 2023), and the organisational and societal implications and challenges of AI adoption (Dwivedi et al., 2021; Romeo & Lacko, 2026).

The constructivist grounded theory supports these perspectives but suggests that recognising the importance and interdependence of socio-technical elements is not sufficient for developing an understanding of the organisational problem. Rather, these elements acquire their meaning and significance through their relationships with one another in practice. For example, understanding the relevance of available data requires examining the work processes through which it is generated, the knowledge needed to interpret it, and the organisational decisions it is intended to support.

This distinction does not question the use of socio-technical systems thinking in AI integration, which emphasises the interdependence of social and technical elements and their joint optimisation (Leavitt, 1965; Fox, 1995; Appelbaum, 1997; Davis et al., 2014; Klein, 2014). However, it extends the use of such perspectives in AI integration research by adopting a more constitutive relational view as explained by sociomateriality (Orlikowski, 2007; Orlikowski & Scott, 2008; Orlikowski, 2010). The contribution, therefore, lies not in identifying

new socio-technical elements or their relationships in AI integration, but in explaining how socio-technical problem-understanding develops in practice through ongoing inquiry into the relationships among these elements, and how these relationships shape the content of what is understood about the organisational problem.

The constitutive nature of socio-technical relationships is also important for understanding the directional development of problem-understanding. Previous research on AI integration has thouroughly established the importance of socio-technical considerations (Makarius et al., 2020; Jarrahi et al., 2023; Lee et al., 2023; Uren & Edwards, 2023). The findings of this thesis extend these perspectives by showing how the meaning and significance of these elements for the organisational problem emerge through their relationships with one another in practice, forming a directional emergence of problem-understanding. For example, identifying limitations in available data provides only a partial understanding of the problem if the work practices that generate the data remain unexplored. Understanding that employees record information differently may reveal that the problem concerns not only data quality, but also how work is performed and information is interpreted within the organisation. The meaning of the data and the work practices is therefore developed through understanding their constitutive relationship in the context of the organisational problem.

This perspective is particularly important regarding the provisional understandings that influence project direction. Previous research has demonstrated that translating organisational objectives into technically actionable problems involves interpretation and negotiation, with consequences for how problems are subsequently approached (Passi & Barocas, 2019; Passi & Sengers, 2020). The findings of this thesis extend these insights by explaining how the extent to which socio-technical relationships are investigated shapes the content of provisional understandings and, consequently, what becomes relevant for continued inquiry. In the example above, understanding the issue primarily as a technical data limitation may direct subsequent activities towards selecting alternative datasets or adjusting predictive models. Investigating its relationship with employees' work practices, however, may instead reveal the need to examine how information is recorded, interpreted, and used in organisational decisions. Thus, different understandings of the same problem may direct subsequent inquiry towards different aspects of its socio-technical relationships.

The theoretical contribution here, therefore, lies mainly in explaining how socio-technical elements and their relationships in AI integration operate in practice. More particularly, it explains how the content of socio-technical problem-understanding may be shaped through inquiry into the constitutive relationships among Technology, Organisation, People, and Process. The risk of insufficiently investigating these relationships is not merely overlooking individual elements but developing a partial understanding of the organisational problem that

may direct subsequent inquiry towards an increasingly narrow interpretation of it.

This highlights the importance of actively and collectively exploring socio-technical constitutive relationships throughout AI integration. However, the extent to which such inquiry can take place also depends on how project activities, responsibilities, and resources are organised. This draws attention to the organising conditions under which socio-technical problem-understanding develops, and to the potential tensions between its emergent nature and the ways AI integration initiatives are organised as projects.

### *7.1.4. From project organising to organising socio-technical inquiry*

Previous research conceptualises projects as temporary forms of organising that coordinate people, resources, and activities towards specific objectives (Lundin & Söderholm, 1995; Packendorff, 1995; Davies & Hobday, 2005). Such arrangements provide important conditions for AI integration, which requires experimentation, learning, adaptation, and cross-functional collaboration (Fountaine et al., 2019; Makarius et al., 2020; Jarrahi et al., 2023). However, previous research also identifies tensions between expectations of predictable project work and the exploratory nature of AI development (Hopf et al., 2023), as well as difficulties in translating organisational objectives into analytically actionable problems (de Mast & Lokkerbol, 2024). The findings of this thesis support these findings while extending attention

to the duality of this, explaining how project organising shapes the continued development of socio-technical problem-understanding, and that the emergence of socio-technical problem-understanding has a shaping effect on organising needs.

Specifically, the final constructivist grounded theory explains how socio-technical problem-understanding unfolds as an emergent and directional process of inquiry into constitutive socio-technical relationships, shaped by the conditions under which this inquiry is organised. Structure, resources, expertise, and direction influence, for example, which relationships can be investigated, whose perspectives contribute to the development of understanding, and which provisional understandings guide subsequent activities. As understanding emerges, new relationships and questions may arise, creating evolving requirements for continued inquiry. This suggests that project organising not only provides structure and coordination for AI development, but could also enable continued socio-technical inquiry by remaining responsive to emerging understandings of the organisational problem. When organising arrangements remain tied to initial assumptions and objectives, opportunities to investigate newly identified relationships may be constrained, potentially reinforcing a narrower understanding of the problem.

The findings therefore do not suggest that project organising is inherently unsuitable for AI integration. Project structures provide necessary coordination and direction, but their suitability depends

partly on their responsiveness to emerging understandings of the organisational problem. Previous research emphasises the importance of flexibility, collaboration, and adaptation in AI implementation (Eklöf et al., 2024) and digital transformation (Sousa & Rocha, 2019). The findings of this thesis support these perspectives while extending the need for adaptability beyond technical development activities to the organisation of socio-technical inquiry itself. Rather than adapting only how an AI solution is developed, project teams may also need to reconsider who participates, which relationships require investigation, how resources are allocated, and whether the project's direction remains relevant as understanding develops.

These findings also align with previous research highlighting the challenges of moving AI initiatives beyond technically feasible pilots towards sustained organisational integration and scaling (Fountaine et al., 2019; Sjödin et al., 2021; Westenberger et al., 2022). The constructivist grounded theory offers a possible explanation for how some of these challenges may already develop during exploratory AI projects. When project organising prioritises demonstrable technical progress, inquiry may increasingly focus on technical feasibility, while the constitutive relationship between socio-technical elements is less explored. As a result, projects may develop technically feasible solutions without adequately understanding how these solutions could create value in organisational practice. Although this thesis does not investigate subsequent implementation or scaling, its findings suggest that some challenges encountered at these later stages may originate in

how socio-technical problem-understanding develops and is organised during earlier project activities.

This theoretical contribution therefore lies in conceptualising project organising as an active condition shaping socio-technical problem-understanding, rather than merely providing the structure within which it occurs, while also suggesting a likewise relationship on the other way: organising conditions shape the opportunities for developing socio-technical problem-understanding, while emerging understandings may reveal the need to reconsider those conditions. The shift from *AI project organising* to *organising socio-technical inquiry* thus emphasises the importance of organising arrangements that can respond to the emergent process and constitutive relational content of problem-understanding.

## 7.2. Practical implications: How STP-AI can be used in practice

The practical implications of this thesis concern how companies can approach AI integration while maintaining an understanding of the organisational problems that technological solutions are intended to address. Although the findings are grounded in predictive AI integration initiatives within manufacturing companies and may therefore be most directly applicable to similar contexts, the use of predictive modelling to address organisational problems extends across industries, suggesting that the theoretical and practical contributions may also be relevant to AI integration initiatives in other organisational settings.

Furthermore, as the challenges of developing socio-technical problem-understanding are not necessarily limited to predictive modelling, the contributions may also offer insights into other types of AI applications, although their applicability requires further investigation. However, this transferability is to further explored.

Previous research has highlighted the challenges organisations face in moving AI initiatives beyond technical experimentation towards implementation, scaling, and organisational value creation (Fountaine et al., 2019; Sjödin et al., 2021). Research has also emphasised the difficulties of translating organisational needs into suitable analytical problems and aligning technological development with organisational processes and practices (Passi & Barocas, 2019; Passi & Sengers, 2020; de Mast & Lokkerbol, 2024).

The final constructivist grounded theory provides a basis for addressing these challenges, and rather than introducing another technical development methodology, the proposed practical framework encourages project teams in AI integration initiatives to continuously consider what they understand about the organisational problem, which socio-technical relationships require further investigation, and how continued inquiry should be organised.

A central implication is that project teams need to be intentional about the direction of their problem-understanding. AI integration often involves complex relationships between technological possibilities, organisational objectives, people, and work processes, and as these

relationships are not necessarily apparent from the outset, project teams cannot be expected to fully define the organisational problem before beginning development. However, this does not mean that inquiry should proceed without direction. Instead, the constructivist grounded theory suggests that teams can use provisional understandings as deliberate reference points for deciding what to investigate next. This is particularly important because the recursive nature of problem-understanding means that each activity influences subsequent inquiry. Without consciously considering this direction, technical experimentation may gradually become the primary basis for continued action, and could, in the worst case, result in *"predictions without use cases"*.

In practice, this means that project teams could periodically step back from their immediate development tasks to reconsider the broader organisational problem. For example, a project team in the manufacturing context developing an AI-based demand forecasting model may become focused on improving prediction accuracy. While this work is important, the project team also needs to consider how the predictions relate to planning decisions, existing work practices and the data related to that, organisational objectives, and the people expected to use them. In addition, there is a need to explore these from the perspective that they derive their meaning from one another in the context of the organisational problem. A highly accurate forecast may therefore have limited organisational value if planning decisions cannot be adjusted based on its predictions.

The Technology, Organisation, People, and Process (TOPP) dimensions provide analytical entry points for investigating these relationships. Their purpose is not to ensure that every possible aspect is examined, but to help project teams identify which relationships are relevant to understanding the problem and which require further investigation. This is particularly important because the meaning of individual elements depends on their relationships with others. For example, limitations in available data may affect not only technical data quality but also how employees record information in everyday work. Investigating these relationships may reveal aspects of the organisational problem that would otherwise remain overlooked.

To support this approach, the practical framework proposes three recurring questions that project teams can use throughout AI integration:

- *What is our current provisional understanding of the organisational problem?* This involves articulating what has been learned, how the relevant socio-technical elements relate to one another, and which assumptions or uncertainties remain.
- *What do we need to investigate next, and why?* This encourages the team to deliberately direct continued inquiry towards relationships and uncertainties that are important for understanding the organisational problem, rather than allowing technical possibilities alone to determine subsequent activities.
- *How should we organise continued inquiry?* This concerns whether the project has the expertise, resources, responsibilities, and arrangements needed to investigate the identified questions, or whether these conditions need to be reconsidered.

These questions are not intended as sequential stages or a checklist to be completed once. Instead, they provide a recurring opportunity for project teams to reflect on their understanding and consciously decide how to proceed. For example, after completing a modelling experiment, a team could arrange a “provisional understanding meeting” to briefly revisit the questions, consider what the results reveal about the organisational problem, whether new socio-technical relationships have become apparent, and what this implies for subsequent activities. This creates an opportunity to develop a directed provisional understanding: a shared interpretation of the problem that provides sufficient direction for continued work while remaining open to reconsideration, suggestively through intentional meetings.

Importantly, the purpose of such reflection is not to stall progress or to repeatedly question every project decision. Rather, directed provisional understandings can help project teams regroup around what they have learned, maintain a shared direction, and adapt their activities without losing momentum. They provide a way to combine the openness required for exploration with the direction needed to make progress. This also suggests that progress should not be assessed solely by completed technical activities or improvements in model performance (unless it is the direct purpose of the project in question). For example, recognising that a prediction does not support the intended organisational decision may represent important progress in understanding the problem, even if it does not immediately advance technical development.

The framework also highlights that continued inquiry may require changes to how the project is organised. As new socio-technical relationships become apparent, the project team may discover that additional expertise, different organising forms, or revised responsibilities are needed. For example, a forecasting project that initially involves data and business people may need to include production planners or operational employees to understand how predictions would influence actual planning decisions. The practical implication is therefore not simply that project organising should be flexible, but that the organisation of the project should remain responsive to what the developing understanding of the problem reveals is needed. Structure, resources, expertise, and direction should support continued socio-technical inquiry.

At the same time, the recursive nature of problem-understanding does not imply that organisational problems must be investigated indefinitely before solutions can be developed. Technical experimentation and solution development are themselves important sources of learning and can proceed alongside inquiry into the organisational problem, in line with ideas by von Hippel and von Krogh (2016). As provisional understandings become sufficiently informed to support decisions, project teams can progressively direct more attention towards developing and implementing potential solutions in the same process. The purpose is therefore not to achieve a complete or final understanding of every socio-technical relationship, but to develop an understanding sufficient to guide meaningful action while remaining

attentive to new information that may challenge earlier assumptions. In this way, the framework supports the movement from exploratory problem-understanding towards solution development without treating the organisational problem as necessarily fixed or fully understood.

Taken together, the practical implications of the final constructivist grounded theory concern how manufacturing project teams can deliberately guide understanding of socio-technical problems as they progress with AI development. By regularly articulating provisional understandings, investigating relevant socio-technical relationships, and reconsidering how continued inquiry is organised, project teams may reduce the drift towards technically focused projects. The framework does not replace established AI development approaches but provides complementary guidance for maintaining attention to the organisational problem throughout development in specific AI initiatives. Its intended value is to support manufacturing companies in pursuing technically feasible solutions that remain connected to the organisational needs, work practices, and human activities they are intended to support. As a practical framework derived from the constructivist grounded theory, its usefulness and effects on AI integration outcomes remain to be evaluated empirically.

## 7.3. Method discussion

The methodological approach enabled both to explore and explain how socio-technical problem-understanding unfolded in practice during AI

integration. A particular strength of the study was the opportunity to follow exploratory AI integration initiatives over time, allowing socio-technical problem-understanding to be examined as a developing process rather than at a single point in time. The observations also made it possible to trace how project teams approached organisational problems, how their understandings developed, and how these understandings influenced the direction of continued work. The subsequent interviews complemented this perspective by providing retrospective reflections on project developments, including consequences and relationships that were not necessarily apparent during the observations. Together, the two phases enabled an analysis of how problem-understanding unfolded over time and how project members subsequently interpreted these developments. Through constant comparison and analytical memo-writing, these insights were progressively integrated into the theoretical explanations.

Another strength was the pragmatist foundation, which informed the research by directing attention towards project members' actions, experiences, and the practical consequences of their activities (Dewey, 1938; Morgan, 2020). This orientation guided both data collection and analysis, encouraging an examination of what project teams did in practice and how their activities recursively built on each other. Constructivist grounded theory provided a systematic yet flexible approach to capturing this through coding, constant comparison, memo-writing, and theoretical integration. The use of sensitising concepts further supported an abductive movement between empirical

observations and existing theoretical perspectives, allowing emerging interpretations to be examined and refined without imposing predefined analytical categories. Together, these approaches enabled the development of a theoretically informed explanation grounded in the empirical material of a complex and initially open-ended phenomenon, while recognising the researcher's active role in constructing and interpreting the findings and in providing a transparent process.

Despite these strengths, several methodological limitations should be acknowledged. First, the empirical material concerned exploratory predictive modelling initiatives in three manufacturing companies, organised as temporary projects. The findings may therefore reflect characteristics of this particular technological, organisational, and industrial context. Although the inclusion of multiple companies provided opportunities for comparison, the study does not establish whether the identified relationships unfold similarly in other industries, AI applications, or forms of organising.

Second, the iterative relationship between observations and interviews involved both opportunities and limitations. The interviews were informed by patterns identified during the observations, enabling further investigation of emerging analytical questions. However, a more developed theoretical analysis of the observational material before conducting the interviews might have enabled more focused investigation of particular categories and relationships. Furthermore, observations and retrospective accounts provided different perspectives

on project activities. While observations offered insights into activities and interactions as they unfolded, interviews reflected project members' subsequent interpretations of their experiences. Although combining these perspectives strengthened the analysis, the resulting explanations remain interpretative.

The use of constructivist grounded theory may also be questioned, given that the research began with an identified problem concerning socio-technical understanding in AI integration. However, constructivist grounded theory does not require researchers to enter the field without prior knowledge or research interests (Charmaz, 2014). Rather, the methodological consideration concerns how these interests influence data collection and analysis. In this study, the initial research problem provided direction for the inquiry, while the analytical categories and their relationships were developed through iterative engagement with the empirical material. Nevertheless, the researcher's initial interests and theoretical perspectives inevitably shaped what received attention and how the findings were interpreted.

Another consideration concerns the distinction between project members' accounts of their activities and the activities themselves. Although the observations provided opportunities to follow project developments over time, much of the empirical material consisted of project members describing and discussing their work, rather than direct observation of all activities within their respective organisations. Similarly, the interviews reflected project members' retrospective

interpretations of their experiences. The findings should therefore be understood as developed from these accounts and observed interactions, rather than as a complete representation of everything that occurred within the projects.

The purpose of the broader research project (TARS) provides important context for interpreting the findings. The initiatives were explicitly concerned with exploring and learning about predictive modelling, making technical experimentation an expected and legitimate focus of project activities. Consequently, the observed emphasis on technical feasibility should not necessarily be interpreted as a failure to address organisational problems. At the same time, the companies also expressed an interest in understanding how predictive modelling could address organisational needs and in avoiding an excessive focus on technical possibilities. The findings, therefore, need to be understood in relation to this dual purpose: developing knowledge of predictive modelling while exploring its organisational relevance. This context may have influenced the direction of project activities and the patterns identified in the analysis.

Finally, the research was conducted during a period of rapid technological development and changing organisational expectations concerning AI. The resulting constructivist grounded theory should therefore be understood in relation to the technological and organisational context in which the research took place. This also influenced how the findings were positioned in relation to existing

research, as the body of knowledge on AI integration developed considerably throughout the study. Consequently, the theoretical contribution reflects both the empirical insights developed during the research and their interpretation within an evolving field of knowledge.

## 7.4. Future research

The findings of this thesis point to several areas for future research, including whether constructivist grounded theory applies in other settings and how it could be developed further. Other areas include how socio-technical understandings of problems change over time, alternative ways to organise projects, and the practical use of the proposed framework.

First, future research could explore socio-technical problem-understanding in other industries, organisations, and AI applications. This study focused on exploratory predictive modelling in manufacturing. Comparative studies could examine whether similar patterns of emerging and provisional understandings, socio-technical relationships, and technical drift occur elsewhere. Comparing projects that explore technological possibilities with those that address specific organisational problems could show how an initiative's initial purpose influences how the problem is understood. Second, future research could develop the theoretical relationships identified in the constructivist grounded theory. It could examine more closely how temporary anchors guide later inquiry, which socio-technical

relationships become important, and how project conditions shape which parts of organisational problems receive attention. Since research on AI integration has grown during the course of this thesis, further engagement with recent studies could help refine, challenge, or extend the proposed explanation. A broader review of how different research areas address problem-understanding, socio-technical relationships, and project organising could also clarify how these ideas interact.

Third, the tension between emerging socio-technical inquiry and bounded project organising points to a need to study other ways of organising AI integration. Future research could examine how project structures, resources, expertise, responsibilities, and goals might change as new understandings of organisational problems develop. Comparing different project arrangements could help identify conditions that support ongoing inquiry while providing enough coordination and direction to keep projects moving. This could also shed light on how organising conditions and problem-understanding influence each other, including how new understandings may create new organising needs. The aim is not to assume that traditional project arrangements are unsuitable, but to explore how different approaches can accommodate the changing and relational nature of socio-technical problem-understanding.

Finally, future research could develop and test the constructivist grounded theory as a practical framework. For example, action research with manufacturing companies could examine whether regular

discussions of socio-technical relationships and provisional understandings help project teams stay focused on organisational problems as they develop technology. Such studies could also assess whether the framework helps teams bring together distributed expertise, adapt project organisation, and avoid unwanted directional emergence.

## 7.5. Conclusions

This thesis explored and explained how socio-technical problem-understanding unfolds in practice during AI integration projects and what shapes its development. Based on studies of exploratory predictive modelling projects in three manufacturing companies, the findings show that problem-understanding is an emergent, recursive, and directional process, shaped by the constitutive relationships among socio-technical elements and the conditions under which inquiry is organised. The theoretical contribution is an integrated constructivist grounded theory explaining how these findings interact and how AI initiatives can be deliberately directional. The practical contribution is a framework supporting deliberate socio-technical inquiry and responsive project organising throughout AI integration.

# Epilogue

The years I have spent working on this research have been crazy, AI-wise. When I began in 2021, AI still felt new, mysterious, and partly beyond the reach of everyday users. Only a year later, OpenAI launched ChatGPT, and several other generative AI platforms followed, now an everyday companion for many, both at work and in their personal lives. Add a few years to that, and some of the very researchers building the most advanced AI systems are publicly warning that AI development may be moving too quickly, and some even argue that increasingly capable AI systems could ultimately pose existential risks to humanity itself within a decade (paraphrasing Sam Altman, CEO of OpenAI, as cited in Booth, October 5, 2026, and Anthropic researchers as reported by Luscombe, September 9, 2026).

Looking back, the speed of this development has also been reflected in the research fields focusing on AI integration. Two periods away from the thesis during parental leave meant returning to what felt like an entirely new AI landscape. Literature and discussions that seemed highly relevant only a year or two earlier quickly lost their prominence as both organisations and researchers increasingly shifted their attention from technological capabilities to questions of organisational readiness, culture, human interaction, and socio-technical integration.

Organisational integration, however, has moved much more slowly, with a considerable gap remaining between the rhetoric around AI

integration and the actual change: the speed of transformation imagined in our 2021 and 2022 research projects and the pace at which organisations have incorporated AI into established work systems.

To place this research in a broader context, a process manager at another large manufacturing firm was asked to comment on the findings and the models it generated. They commented that *"today, we mostly talk about AI as a technology. We almost never talk about everything else."* This further emphasises the gap between what we *think* we can do and what we can *actually* do with AI. The process manager continues this line of thought, linking it to a hype-driven and somewhat unjustified level of value assigned to data: *"Someone often has an idea and a lot of faith in the data. The assumption is that if we have data, then we can do AI. But nobody really knows."* This is also reflected in the findings of this research. They continuously described how discussions around AI initiatives often begin with statements such as: *"We have a lot of data about this, and it is well structured. We could use AI for this."* Yet their own response was typically different: *"Does the organisation actually want to use AI in that process? How would that work? Who has the interest and the knowledge?"*

Looking back, I find that these questions capture much of what this thesis has sought to explore. AI integration cannot be reduced to a question of whether a technical solution can be built and if we have the data for it. Still, this is where organisations most often start. Another reflection concerned the processual nature of AI integration, where the

process manager noted that the process model developed in this thesis resembled established approaches to optimisation and continuous improvement, but also highlighted an important difference: *"When we work with optimisation, there is usually an end point. AI does not seem to have that in the same way."* Rather than representing a discrete project, AI was described as *"a broader change in how work systems are designed."* This observation echoes one of the central insights emerging from the research: that AI integration often involves ongoing inquiry, adaptation, and redesign rather than implementation followed by stability. Organisations recognise the tension, yet they continue to organise these initiatives as projects with a start and an end. In other words, it can be suggested that they need structure and coordination, along with ways to make sense of their work and at the same time, AI development seems to call for experimentation that resists formalisation. The process manager commented on this, saying *"we are kind of stuck in our established ways of thinking and working"*.

While it is not intended as a solution, the constructivist grounded theory developed in this research may offer one way of approaching these challenges. At the same time, the process manager cautioned against treating all AI initiatives as the same. *"You have to distinguish between small and large AI initiatives because they create very different conditions."* Some, perhaps smaller, initiatives may generate useful outcomes almost immediately, while others require repeated cycles of experimentation and learning. This reminder is important. The models presented in this thesis should not be understood as rigid procedures,

but rather as ways of structuring inquiry while remaining open to revision and change.

But the tension arising from the challenges of AI integration in organisations still poses some foundational questions, and my final reflection is this: Perhaps there is something in the idea that the cognitive support forms of AI are, at their core, technology that learns and develops at the level of the individual user, and that this does not always align easily with the realities of organisational life. Organisations, by their nature, require coordination, structure, and shared ways of working across many individuals, yet the experimental nature of contemporary AI development often resists such structure.

At the same time, it is striking how strongly organisations continue to believe in the transformative potential of AI, despite relatively few examples of large-scale organisational value creation. Throughout this research, organisations have been remarkably willing to share experiences, lessons learned, and ongoing AI initiatives, while simultaneously asking for successful examples from others. This suggests that many organisations still view AI integration as an exploratory and uncertain endeavour. Stable best practices have yet to emerge, though there is hope they will soon.

How, then, should organisations approach this challenge? I do not claim that the constructivist grounded theory developed in this thesis provides the answer. However, I believe there is something important in recognising the tension between the highly experimental nature of AI

development and organisations' need for structure, coordination, and a sense of direction. The challenge may not be to eliminate this tension, but to work productively with it. It may even be that some AI technologies are difficult, or perhaps impossible, to integrate within existing organisational arrangements. Equally, many organisations may remain deeply shaped by established ways of working, making it difficult to fully engage with the opportunities and challenges AI presents. Regardless of where this development leads, it will be fascinating to continue following it.

# References


Adobor, H. (2026). Navigating the AI adoption trap: A framework for organizational practice. *Organizational Dynamics*, *55*(2), Article 101232. https://doi.org/10.1016/j.orgdyn.2026.101232

Appelbaum, S. H. (1997). Socio-technical systems theory: An intervention strategy for organizational development. *Management Decision*, *35*(6), 452–463. https://doi.org/10.1108/00251749710173823

Basadur, M., Graen, G. B., & Green, S. G. (1982). Training in creative problem solving: Effects on ideation and problem finding and solving in an industrial research organization. *Organizational Behavior and Human Performance, 30*(1), 41–70. https://doi.org/10.1016/0030-5073(82)90233-1

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly, 45*(3), 1433-1450. https://doi.org/10.25300/MISQ/2021/16274

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can machines learn, and what does it mean for occupations and the economy? *AEA Papers and Proceedings, 108*, 43–47. https://doi.org/10.1257/pandp.20181019

Booth, R. (2026, October 5). Accept 'bad things' in return for benefits of AI, says Sam Altman. *The Guardian*

Challapally, A., Pease, C., Raskar, R., & Chari, P. (2025). *The GenAI divide: State of AI in business 2025*. Massachusetts Institute of Technology, Project NANDA. https://mlq.ai/media/quarterly_decks/v0.1_State_of_AI_in_Business_2025_Report.pdf

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., & Wirth, R. (2000). *CRISP-DM 1.0: Step-by-step data mining guide*. SPSS

Charmaz, K. (2005). Grounded theory in the 21st century: Applications for advancing social justice studies. In N. K. Denzin & Y. S. Lincoln (Eds.),

*The SAGE handbook of qualitative research* (3rd ed., pp. 507–535). SAGE Publications.

Charmaz, K. (2008). Constructionism and the grounded theory method. In J. A. Holstein & J. F. Gubrium (Eds.), *Handbook of constructionist research* (pp. 397–412). The Guilford Press.

Charmaz, K. (2014). *Constructing grounded theory* (2nd ed.). SAGE Publications.

Charmaz, K. (2017). The power of constructivist grounded theory for critical inquiry. *Qualitative Inquiry*, *23*(1), 34–45. https://doi.org/10.1177/1077800416657105

Cherryholmes, C. H. (1992). Notes on pragmatism and scientific realism. *Educational Researcher*, *21*(6), 13–17. https://doi.org/10.2307/1176502

Chirumalla, K., Oghazi, P., Nnewuku, R. E., Tuncay, H., & Yahyapour, N. (2025). Critical factors affecting digital transformation in manufacturing companies. *International Entrepreneurship and Management Journal, 21*, Article 54. https://doi.org/10.1007/s11365-024-01056-3

Chun Tie, Y., Birks, M., & Francis, K. (2019). Grounded theory research: A design framework for novice researchers. *SAGE Open Medicine, 7*, 1–8. https://doi.org/10.1177/2050312118822927

Cohen, M. D., March, J. G., & Olsen, J. P. (1972). A garbage can model of organizational choice. *Administrative Science Quarterly, 17*(1), 1–25. https://doi.org/10.2307/2392088

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

D'Zurilla, T. J., & Goldfried, M. R. (1971). Problem solving and behavior modification. *Journal of Abnormal Psychology, 78*(1), 107–126. https://doi.org/10.1037/h0031360

Davenport, T. H., & Ronanki, R. (2018, January-February). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108–116.

Davies, A., & Hobday, M. (2005). *The business of projects: Managing innovation in complex products and systems*. Cambridge University Press. https://doi.org/10.1017/CBO9780511493294

Davis, M. C., Challenger, R., Jayewardene, D. N., & Clegg, C. W. (2014). Advancing socio-technical systems thinking: A call for bravery. *Applied Ergonomics, 45*(2), 171-180. https://doi.org/10.1016/j.apergo.2013.02.009

de Mast, J., & Lokkerbol, J. (2024). DAPS diagrams for defining data science projects. *Journal of Big Data, 11*, Article 50. https://doi.org/10.1186/s40537-024-00916-7

Denscombe, M. (2014). *The good research guide: For small-scale social research projects* (5th ed.). Open University Press.

Denzin, N. K., & Lincoln, Y. S. (Eds.). (2011). *The SAGE handbook of qualitative research* (4th ed.). SAGE Publications.

Dewey, J. (1938). *Logic: The theory of inquiry*. Henry Holt and Company.

Dorst, K. (2011). The core of 'design thinking' and its application. *Design Studies, 32*(6), 521–532. https://doi.org/10.1016/j.destud.2011.07.006

Dunbar, K. (1998). Problem solving. In W. Bechtel & G. Graham (Eds.), *A companion to cognitive science* (pp. 289–298). Blackwell.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Eklöf, J., Lundh Snis, U., Hamelryck, T. W., Grima, A., & Rønning, O. (2024). AI implementation and capability development in manufacturing: An action research case. *Proceedings of the 57th Hawaii International Conference on System Sciences*, 5796–5805. https://aisel.aisnet.org/hicss-57/os/ai_and_organizing/3/

Encyclopaedia Britannica. (n.d.-a). Problem. In *The Britannica Dictionary*. Retrieved October 8, 2026, from https://www.britannica.com/dictionary/problem

Encyclopaedia Britannica. (n.d.-b). Understanding. In *The Britannica Dictionary*. Retrieved October 8, 2026, from https://www.britannica.com/dictionary/understanding

European Parliament & Council of the European Union. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). *Official Journal of the European Union, L*, 2024/1689.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005

Fountaine, T., McCarthy, B., & Saleh, T. (2019, July-August). Building the AI-powered organization. *Harvard Business Review*, *97*(4), 62–73.

Fox, W. M. (1995). Sociotechnical system principles and guidelines: Past and present. *The Journal of Applied Behavioral Science, 31*(1), 91–105. https://doi.org/10.1177/0021886395311009

Frensch, P. A., & Funke, J. (1995). Definitions, traditions, and a general framework for understanding complex problem solving. In P. A. Frensch & J. Funke (Eds.), *Complex problem solving: The European perspective* (pp. 3–25). Lawrence Erlbaum Associates.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gemünden, H. G., Lehner, P., & Kock, A. (2018). The project-oriented organization and its contribution to innovation. *International Journal of Project Management*, *36*(1), 147–160. https://doi.org/10.1016/j.ijproman.2017.07.009

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies for qualitative research*. Aldine Publishing Company.

Haefner, N., Parida, V., Gassmann, O., & Wincent, J. (2023). Implementing and scaling artificial intelligence: A review, framework, and research agenda. *Technological Forecasting and Social Change*, *197*, 122878. https://doi.org/10.1016/j.techfore.2023.122878

Hopf, K., Müller, O., Shollo, A., & Thiess, T. (2023). Organizational implementation of AI: Craft and mechanical work. *California Management Review,* *66*(1), 23–47. https://doi.org/10.1177/00081256231197445

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jarrahi, M. H., Lutz, C., Boyd, K., Oesterlund, C., & Willis, M. (2023). Artificial intelligence in the work context. *Journal of the Association for Information Science and Technology*, *74*(3), 303–310. https://doi.org/10.1002/asi.24730

Johnson, R. B., & Walsh, I. (2019). Mixed grounded theory: Merging grounded theory with mixed methods and multimethod research. In A. Bryant & K. Charmaz (Eds.), *The SAGE handbook of current developments in grounded theory* (pp. 517-531). SAGE Publications. https://doi.org/10.4135/9781526436061.n27

Joksimovic, S., Ifenthaler, D., Marrone, R., De Laat, M., & Siemens, G. (2023). Opportunities of artificial intelligence for supporting complex problem-solving: Findings from a scoping review. *Computers and Education: Artificial Intelligence,* *4*, Article 100138. https://doi.org/10.1016/j.caeai.2023.100138

Jonassen, D. H. (1997). Instructional design models for well-structured and ill-structured problem-solving learning outcomes. *Educational Technology Research and Development*, *45*(1), 65–94. https://doi.org/10.1007/BF02299613

Jönköping University Library. (2026.-a). *Informationssökning*. https://ju.se/bibliotek/ansvarsfull-anvandning-av-ai/informationssokning.html

Jönköping University Library. (2026.-b). *Källkritik*. https://ju.se/bibliotek/ansvarsfull-anvandning-av-ai/kallkritik.html

Jönköping University Library. (2026.-c). *Skrivande*. https://ju.se/bibliotek/ansvarsfull-anvandning-av-ai/skrivande.html

Klein, L. (2014). What do we actually mean by "sociotechnical"? On values, boundaries and the problems of language. *Applied Ergonomics*, *45*(2), 137–142. https://doi.org/10.1016/j.apergo.2013.03.027

Koen, P., Ajamian, G., Burkart, R., Clamen, A., Davidson, J., D'Amore, R., Elkins, C., Herald, K., Incorvia, M., Johnson, A., Karol, R., Seibert, R., Slavejkov, A., & Wagner, K. (2001). Providing clarity and a common language to the "fuzzy front end". *Research-Technology Management*, *44*(2), 46–55. https://doi.org/10.1080/08956308.2001.11671418.

Leavitt, H. J. (1965). Applied organizational change in industry: Structural, technological and humanistic approaches. In J. G. March (Ed.), *Handbook of organizations* (pp. 1144–1170). Rand McNally.

Lee, M. C. M., Scheepers, H., Lui, A. K. H., & Ngai, E. W. T. (2023). The implementation of artificial intelligence in organizations: A systematic literature review. *Information & Management, 60*(5), Article 103816. https://doi.org/10.1016/j.im.2023.103816

Lempert, L. B. (2007). Asking questions of the data: Memo writing in the grounded theory tradition. In A. Bryant & K. Charmaz (Eds.), *The SAGE handbook of grounded theory* (pp. 245–264). SAGE Publications. https://doi.org/10.4135/9781848607941.n12

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. SAGE Publications.

Lundin, R. A., & Söderholm, A. (1995). A theory of the temporary organization. *Scandinavian Journal of Management*, *11*(4), 437–455. https://doi.org/10.1016/0956-5221(95)00036-U

Luscombe, R. (2026, September 9). Anthropic researchers say AI could cause human extinction by 2030. *The Guardian*.

Magistretti, S., Pham, C. T. A., & Dell'Era, C. (2025). The creative process of problem framing for innovation: An integrative review and research

agenda. *Journal of Product Innovation Management*, *42*(6), 987–1018. https://doi.org/10.1111/jpim.12783

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research, 120*, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Merriam-Webster. (n.d.-a). Problem. In *Merriam-Webster.com dictionary*. Retrieved October 8, 2026, from https://www.merriam-webster.com/dictionary/problem

Merriam-Webster. (n.d.-b). Understanding. In *Merriam-Webster.com dictionary*. Retrieved October 8, 2026, from https://www.merriam-webster.com/dictionary/understanding

Midler, C. (1995). "Projectification" of the firm: The Renault case. *Scandinavian Journal of Management*, *11*(4), 363–375. https://doi.org/10.1016/0956-5221(95)00035-6

Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook* (3rd ed.). SAGE Publications.

Mohaghegh, M., & Furlan, A. (2020). Systematic problem-solving and its antecedents: A synthesis of the literature. *Management Research Review, 43*(9), 1033–1062. https://doi.org/10.1108/MRR-06-2019-0284

Mohlin, A. (2023). How to facilitate manufacturing industry learning from problems: A review on advanced technology problem-solving. *Journal of Workplace Learning*, *35*(6), 470–489. https://doi.org/10.1108/JWL-01-2023-0008

Morgan, D. L. (2020). Pragmatism as a basis for grounded theory. *The Qualitative Report*, *25*(1), 64–73. https://doi.org/10.46743/2160-3715/2020.3993

Mumford, M. D., Reiter-Palmon, R., & Redmond, M. R. (1994). Problem construction and cognition: Applying problem representations in ill-defined domains. In M. A. Runco (Ed.), *Problem finding, problem solving, and creativity* (pp. 3–39). Ablex Publishing.

Newell, A., & Simon, H. A. (1972). *Human problem solving*. Prentice-Hall.

Niehaus, F., & Wiesche, M. (2021). A socio-technical perspective on organizational interaction with AI: A literature review. In *ECIS 2021 Research Papers*. https://aisel.aisnet.org/ecis2021_rp/156/

Orlikowski, W. J. (2007). Sociomaterial practices: Exploring technology at work. *Organization Studies*, *28*(9), 1435–1448. https://doi.org/10.1177/0170840607081138

Orlikowski, W. J. (2010). The sociomateriality of organisational life: Considering technology in management research. *Cambridge Journal of Economics*, *34*(1), 125–141. https://doi.org/10.1093/cje/bep058

Orlikowski, W. J., & Gash, D. C. (1994). Technological frames: Making sense of information technology in organizations. *ACM Transactions on Information Systems*, *12*(2), 174–207. https://doi.org/10.1145/196734.196745

Orlikowski, W. J., & Scott, S. V. (2008). Sociomateriality: Challenging the separation of technology, work and organization. *Academy of Management Annals*, *2*(1), 433–474. https://doi.org/10.1080/19416520802211644

Passi, S., & Barocas, S. (2019). Problem formulation and fairness. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 39–48). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287567

Passi, S., & Sengers, P. (2020). Making data science systems work. *Big Data & Society, 7*(2), 1–13. https://doi.org/10.1177/2053951720939605

PwC. (2021, October 27). *Operationalizing artificial intelligence: Making the promise a reality*. Harvard Business Review. https://hbr.org/sponsored/2021/10/operationalizing-artificial-intelligence-making-the-promise-a-reality

Raftopoulos, M. (2024). Organizational challenges in adoption and implementation of artificial intelligence. In T. X. Bui (Ed.), *Proceedings of the 57th Hawaii International Conference on System Sciences* (pp. 5786–5795). Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2024.698

Reid, S. E., & De Brentani, U. (2004). The fuzzy front end of new product development for discontinuous innovations: A theoretical model. *Journal of Product Innovation Management*, *21*(3), 170–184. https://doi.org/10.1111/j.0737-6782.2004.00068.x

Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences*, *4*(2), 155–169. https://doi.org/10.1007/BF01405730

Romeo, E., & Lacko, J. (2026). Adoption and integration of AI in organizations: A systematic review of challenges and drivers towards future directions of research. *Kybernetes*, *55*(3), 1286–1307. https://doi.org/10.1108/K-07-2024-2002

Russell, S. J., & Norvig, P. (2010). *Artificial intelligence: A modern approach* (3rd ed.). Prentice Hall.

Schön, D. A. (1983). *The reflective practitioner: How professionals think in action*. Basic Books.

Selbst, A. D., boyd, d., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and abstraction in sociotechnical systems. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 59–68). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287598

Simon, H. A., & Hayes, J. R. (1976). The understanding process: Problem isomorphs. *Cognitive Psychology, 8*(2), 165–190. https://doi.org/10.1016/0010-0285(76)90022-0

Singla, A., Sukharevsky, A., Hall, B., Yee, L., & Chui, M. (2025, November 5). *The state of AI in 2025: Agents, innovation, and transformation.* McKinsey & Company. https://www.mckinsey.com/featured-insights/artificial-intelligence/the-state-of-ai-2025

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research, 134*, 574–587. https://doi.org/10.1016/j.jbusres.2021.05.009

Spear, S., & Bowen, H. K. (1999, September-October). Decoding the DNA of the Toyota Production System. *Harvard Business Review*, *77*(5), 96–106.

Sousa, M. J., & Rocha, Á. (2019). Digital learning: Developing skills for digital transformation of organizations. *Future Generation Computer Systems, 91*, 327–334. https://doi.org/10.1016/j.future.2018.08.048

Stern, P. N. (2007). On solid ground: Essential properties for growing grounded theory. In A. Bryant & K. Charmaz (Eds.), *The SAGE handbook of grounded theory* (pp. 114–126). SAGE Publications.

Sturm, T., Fecho, M., & Buxmann, P. (2021). To use or not to use artificial intelligence? A framework for the ideation and evaluation of problems to be solved with artificial intelligence. In *Proceedings of the 54th Hawaii International Conference on System Sciences* (pp. 206–215). Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2021.023

Swedish Research Council. (2017). *Good research practice*. https://www.vr.se/download/18.5639980c162791bbfe697882/1555334908942/Good-Research-Practice_VR_2017.pdf

Sydow, J., & Windeler, A. (2020). Temporary organizing and permanent contexts. *Current Sociology*, *68*(4), 480–498. https://doi.org/10.1177/0011392120907629

Szczepanski, M. (2019). *Economic impacts of artificial intelligence (AI)* (PE 637.967). European Parliamentary Research Service. https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI%282019%29637967

Säfsten, K., & Gustavsson, M. (2020). *Research methodology: For engineers and other problem-solvers* (R. Ehnsiö, Trans.). Studentlitteratur. (Original work published 2019)

Thornberg, R. (2012). Informed grounded theory. *Scandinavian Journal of Educational Research*, *56*(3), 243–259. https://doi.org/10.1080/00313831.2011.581686

Thun, S., Bakås, O., & Storholmen, T. C. B. (2022). Development and implementation processes of digitalization in engineer-to-order

manufacturing: Enablers and barriers. *AI & Society, 37*, 725–743. https://doi.org/10.1007/s00146-021-01174-4

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. An examination of the psychological situation and defences of a work group in relation to the social structure and technological content of the work system. *Human Relations, 4*(1), 3–38. https://doi.org/10.1177/001872675100400101

Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, *68*, Article 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588

Vaccaro, A., Brusoni, S., & Veloso, F. M. (2011). Virtual design, problem framing, and innovation: An empirical study in the automotive industry. *Journal of Management Studies, 48*(1), 99–122. https://doi.org/10.1111/j.1467-6486.2010.00939.x

von Hippel, E., & von Krogh, G. (2016). CROSSROADS—Identifying viable "need–solution pairs": Problem solving without problem formulation. *Organization Science, 27*(1), 207–221. https://doi.org/10.1287/orsc.2015.1023

Weick, K. E. (1995). *Sensemaking in organizations*. SAGE Publications.

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. *Organization Science*, *16*(4), 409–421. https://doi.org/10.1287/orsc.1050.0133

Westenberger, J., Schuler, K., & Schlegel, D. (2022). Failure of AI projects: Understanding the critical factors. *Procedia Computer Science, 196*, 69–76. https://doi.org/10.1016/j.procs.2021.11.074

Womack, J. P., & Jones, D. T. (1996). *Lean thinking: Banish waste and create wealth in your corporation*. Simon & Schuster.

Yan, J., Liu, Z., Leng, J., Zhao, J. L., Chen, C., Zhang, D., Tao, Y., Wang, Y., Liu, T., Zhang, C., Tong, Y., Mourtzis, D., & Wang, L. (2025). Human-centric artificial intelligence towards Industry 5.0: Retrospect and

prospect. *Journal of Industrial Information Integration*, *47*, Article 100903. https://doi.org/10.1016/j.jii.2025.100903

# Appendix A. Memos in observation analysis

| MEMO CATEGORY | MEMOS |
|---|---|
| **Project purpose and goals** | The choice of project case appear to be data-driven |
| | Display a clear image of "what we want in the end" |
| | Includes "why" they want a certain prediction - but why? |
| | Who is going to explain what we want? If neither the data scientist person nor the business person can do this, how do we know that we have chosen a proper case? |
| | By choosing a case based on technical aspects connects back to not being specific when describing how the system is supposed to be used |
| **Socio-technical imbalance** | It is acceptable not understanding the process (business case), however a sense of urgency in understanding everything about the data and model |
| | Very clear where resources are put - data extraction, data preparation, model testing |
| | They think they understand their case, however are only capable of describing it from a process perspective - miss important elements |
| | Underlying stress to get a "good" model first, and then expect it to be easy to solve the organizational bits? |
| | It seems acceptable to not understand the "soft" aspects but highly important to understand the data aspects |
| | How can a potential goal balance between technology and organization? |
| | Is the balance between data-understanding and business-understanding too difficult? Is it easier to focus on the data? |
| | It seems difficult to find the balance between talking technical and organisational in the research project |
| | Company comments: the hard part is not to solve the problem, the hard part is to get the system out in the organisation |
| **Contextual factors matter** | Decision situations are of focus of the research project |
| | Forecasting and time series main area of focus |
| | Project based on iterations from CRISP |
| | Research project of technical character |
| | Companies have a lot of statistics of current process |
| | Description of "business understanding" in CRISP-framework is in some situations technical, others very thorough and organizational |
| | Important to note that this is a data science project - obviously they are going to focus on data |
| | Is the problem-solving rush a distinct feature of manufacturing industry? |
| **Issues in understanding what they want** | Business case defined by only one sentence in presentation |
| | Describing the same thing (business case) but uses ML-task - also just one sentence |
| | Business case defined by only one sentence in presentation |
| | Describes the business case by setting requirement/goal with prediction |
| | Some companies develop their business case description as the research project proceeds |
| | Reflections from the early stages in previous project includes needing more work |
| | Reflections from previous project includes "how is the system supposed to be used" and "what is it that we really want to predict" |
| | Could it be a better idea to do some kind of visualization/mapping of chosen case instead of just with word? |
| | Having trouble following the instruction "precisice how a finished system can be used", who is going to use the system? |
| | How can we "ask the right questions early"? |
| | Company bringing up "end user experience" - how can this be done in beforehand? |
| | Reflections that they had misunderstandings during start up phase that affected rest of project |
| | Gap between the chosen project case description and data |

# Appendix B. Memos for interview analysis

| Memo category | Memos |
|---|---|
| **Moving problem-understanding** | Iteration unplannable? |
| | Combination of competence + data + value only becomes clear through testing |
| | Need to see almost the whole path to decide early |
| | May need to start from use and work backwards |
| | Early problem-understanding evolves over time |
| | Iteration starts experimental, then becomes structured |
| | Problems are not re-checked or aligned |
| | If no goal is defined, it keeps shifting |
| **Technology focus** | Easy to focus on technology due to immediate feedback |
| | Excitement about technology overshadows problem-understanding |
| | Problem-understanding is given less attention than technology |
| **Multiple aspects of problem need to align** | Data, competence, and business need must all be present, having only 2 of 3 is not enough |
| | Assumption that competence alone will solve everything |
| | Uncertainty about having the right data and knowledge |
| | A good AI case is not enough—business value is needed |
| | Difficulty determining if data is sufficient from the start |
| **Expertise fragmentation** | Too much siloed knowledge |
| | Lack of understanding across domains (data vs process) |
| | Difficulty judging if AI fits the problem |
| | Organization lacks shared understanding of processes |
| | Question of whether hybrid competence is required |
| | Implicit knowledge concentrated in individuals |
| **Organising difficulties** | AI projects do not follow traditional project logic |
| | More like transformation than a project |
| | Heavy dependence on project organization |
| | Lack of structure for time and scope estimation |
| | Not something that can be done as a side project |
| | Need for cross-functional organizing |
| | Many actors required to keep knowledge flowing |
| **Common ground absence** | No shared initial understanding of the project |
| | No clear or stable goal |
| | Unclear what form the problem should take (sentence, use case, etc.) |
| | Need for shared goal and common understanding before starting |
| | Need to ensure everyone understands the project |
| | No socio-technical perspective from the start |
| **Individual dependence** | Reliance on champions/enthusiasts |
| | Projects driven by curiosity rather than value |
| | Question if projects should continue without a strong driver |
| | Projects become vulnerable when tied to individuals |
| | Too complex if dependent on few people |
| | Importance of team stability and continuity |
| **Documentation needed** | Documentation of process and goals is necessary |
| | Documentation makes projects transferable and less vulnerable |
| | Documentation enables communication |
| | Level of use case depends on project maturity |
| **Data understanding important** | Everything depends on better understanding of data |
| | You don't know in advance which data matters |
| | Organization must understand what data is valuable |
| | More stored data enables experimentation |
| **Benchmark need** | Few examples to benchmark against |
| | Hard to judge if ideas are too big |
| | Lack of established frameworks for AI projects |
| | Need for more exploration before starting |
| | Desire for structure despite lack of guidance |
| | Curiosity/passion disrupts structure |

# Appendix C: Observation and interview participants

| | Company role/function | Company | Interviewed? Y/N |
|---|---|---|---|
| 1 | Assistant professor computer science | University | Y |
| 2 | Professor computer science | University | N |
| 3 | Lecturer Computer science | University | Y |
| 4 | Assistant professor Supply chain and operations management | University | N |
| 5 | Professor Supply chain and operations management | University | N |
| 6 | Process developer | Bishop | Y |
| 7 | Global Process leader/master data | Bishop | Y |
| 8 | Operations development | Bishop | N |
| 9 | Digital Process Coordinator | Bishop | N |
| 10 | Improvement of performance manager | Bishop | N |
| 11 | Analytics and automation | Bishop | Y |
| 12 | Logistics manager | Wall-E | Y |
| 13 | System developer | Wall-E | Y |
| 14 | Demand management | C-3PO | Y |
| 15 | Data Analyst | C-3PO | N |
| 16 | Planning specialist (turned data analyst) | C-3PO | Y |

# Appendix D. Interview guide

## Interview questions

### TARS PROJECT

- Tell me about the project in general from start to finish, everything you remember.
- What would you say were the biggest challenges from an organisational perspective? From a process perspective? From a data analysis perspective?
- What were the most important lessons from the project?
- What happened to the project after TARS?

### PROBLEM-UNDERSTANDING

- Tell me about the first phases of the project, everything you remember.
- Is there anything you could have done differently there?
- What were the most important lessons from this phase?
- What would you say were the biggest challenges in this phase from an organisational perspective? From a process perspective? From a data analysis perspective?

### FUTURE

- How would you work with AI projects in the future?
- What lessons have you learned from the project?
- Is there anything else you'd like to add here before we wrap up?

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# Socio-Technical Problem-Understanding in AI Integration Projects

Integrating artificial intelligence (AI) into organisational practices involves more than developing suitable technical solutions; it also requires understanding the organisational problems AI initiatives are intended to address and the socio-technical relationships involved. However, organisational problems are not necessarily fully understood from the outset and may evolve as new knowledge and technological possibilities emerge. Against this background, this thesis explores how socio-technical problem-understanding unfolds in practice and what shapes its development during AI integration projects. Adopting a pragmatist perspective and a constructivist grounded theory methodology, the research draws on empirical studies of exploratory AI integration projects involving predictive modelling in three manufacturing companies. Data were collected through observations and interviews and analysed through constructivist grounded theory procedures.

The study generated three main findings. First, socio-technical problem-understanding unfolds as an emergent, recursive, and directional process, in which temporary anchors enable provisional understandings that guide subsequent inquiry and may progressively direct attention different aspects of the problem. Second, socio-technical problem-understanding concerns the constitutive relationships among technology, organisation, people, and processes, whose meaning emerges from their interrelations within the organisational problem. Third, the conditions under which AI integration projects are organised shape the development and direction of problem-understanding by influencing the space within which socio-technical problem-understanding can emerge, while these emerging understandings may, in turn, create new requirements for how continued inquiry is organised.

Through these findings, the thesis contributes an integrated, constructivist-grounded theory explaining socio-technical problem-understanding in AI integration projects and offers a practical framework to support continuous inquiry into organisational problems and their socio-technical relationships.

Alice Mohlin is a researcher and teacher at the Department of Supply Chain and Operations Management, School of Engineering, Jönköping University. She holds a master's degree in Information Systems from Linnaeus University. During her doctoral studies, she has been involved in research projects focusing on AI readiness and proactive organising for AI transformation. Her research interests centre on how people and organisations navigate and adapt to the introduction and integration of advanced technologies, particularly artificial intelligence (AI).

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