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How Organizations Gain Value from Artificial Intelligence

par
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Résumé

Nous vivons à une époque de développement technologique rapide, dont un des moteurs est l'intelligence artificielle (IA), définie dans cette thèse comme « la frontière des avancées informatiques qui fait référence à l'intelligence humaine pour résoudre des problèmes décisionnels toujours plus complexes » (Berente et al., 2021 : 1435). Cette frontière en constante évolution se concentre actuellement sur l'apprentissage automatique qui permet la prédiction et la prise de décision basées sur les données. L'IA a le potentiel d'augmenter la productivité et la compétitivité des organisations, mais il faut d'abord savoir comment en tirer de la valeur. De nombreuses organisations peinent différencier entre les possibilités et la réalité des solutions basées sur l'IA. Face aux promesses de l'IA et à ses possibilités de création de valeur organisationnelle, ainsi qu'aux défis liés à l'intégration de systèmes d'IA, la question de recherche globale de cette thèse est : Comment les organisations tirent-elles de la valeur de l'IA ?

Pour tirer de la valeur de l'IA, les organisations ont besoin d'une vision stratégique et de pratiques de gestion de projet appropriées pour développer et implanter ces systèmes. Cette thèse explore ces deux perspectives à travers trois essais. **L'essai 1** examine la création de valeur par l'IA d'un point de vue stratégique. Cette étude conceptuelle explore comment l'alignement entre les composants des systèmes d'IA générative et les sources d'autorité religieuse contribue au potentiel de création de valeur de l'IA générative. L'essai adopte une perspective configurationnelle de l'alignement entre les facteurs organisationnels et les ressources informatiques et propose que cet alignement permette la création de valeur par l'IA. Il met également en évidence la contribution de l'IA à la création de valeur religieuse, donc non monétaire. **L'essai 2** examine comment les pratiques de gestion de projet peuvent contribuer à la création de valeur par l'IA. Il s'agit d'une étude de cas d'un projet de développement d'IA ayant généré de la valeur pour de multiples parties prenantes. L'essai 2 utilise la théorie de l'adaptation au niveau de l'équipe comme cadre théorique pour comprendre comment les organisations gèrent les sources de stress liées à un projet d'IA rapide dans un écosystème complexe. Ses quatre propositions théoriques expliquent comment trois pratiques de gestion de projet aident les organisations à gérer ces sources de stress. **L'essai 3** contribue à la perspective de gestion de projet et à la perspective stratégique. Il s'agit d'une méta-synthèse de 12 études de cas qualitatives sur le développement et l'implantation de systèmes d'IA. Grâce à un compte rendu détaillé du processus de développement et de l'implantation de l'IA, il contribue à une meilleure compréhension des pratiques de gestion de projet utilisées tout au long de ce processus. Il fournit une compréhension détaillée de comment les caractéristiques de l'IA posent des défis lors de l'implantation de systèmes d'IA, contribuant à la perspective stratégique de la création de valeur par l'IA. Il explique également comment certaines pratiques de gestion de projet peuvent aider à relever les défis posés par les systèmes d'IA, contribuant ainsi théorisation future de ce domaine.

Mots clés : Intelligence artificielle, IA, valeur générée par l'IA, développement de l'IA, implantation de l'IA, recherche conceptuelle, théorisation configurationnelle, recherche qualitative, étude de cas, revue de littérature, méta-synthèse qualitative.

Méthodes de recherche : recherche conceptuelle, théorisation configurationnelle, recherche qualitative, étude de cas, revue de littérature, méta-synthèse qualitative

Abstract

We are living in an age of rapid technological development, with artificial intelligence (AI) being one of the significant areas of advancement. In this thesis, AI is defined as "*the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems*" (Berente *et al.,* 2021 : 1435). This constantly moving frontier currently focuses on data-driven prediction and decision making using autonomous computer programs which often involve machine learning. AI has the potential to increase organizational productivity and competitivity. However, gaining value from AI is not always easy. Many organizations struggle to distinguish between the hype and the reality of AI-based solutions. Against the backdrop of the promises of AI and the potential opportunities for AI to generate organizational value, coupled with the difficulties faced by organizations when attempting to integrate AI systems, the overall research question of this thesis is *How do organizations gain value from AI?*

To gain value from AI, organizations require both a strategic vision and appropriate project management practices for developing and implementing these systems. This thesis explores both the strategic and project management perspectives to answering this research question through a three-essay approach. **Essay 1** examines value generation from AI from a strategic perspective. It is a conceptual study of how the fit between components of GenAI systems and layers of religious authority contributes to the value creation potential of GenAI. It builds on and extends previous research on the business value of IT by taking a configurational perspective of fit and disaggregating certain constructs from the ISBV framework; it illustrates one way organizational factors and IT resources must fit together to allow for value generation from AI; and by exploring religious value generation, it highlights how AI can contribute to non-monetary value. **Essay 2** examines how project management practices can contribute to value generation from AI. It is a single case study of an AI development project through which value was generated for multiple stakeholders. Essay 2 uses team-level coping theory as a theoretical framework to understand how organizations cope with the stressors of a rapid AI project in a complex ecosystem. It offers four theoretical propositions that explain how three project management practices help organizations address these stressors. **Essay 3** contributes primarily to the project management perspective, but also to the strategic perspective. It is a meta-synthesis of 12 published qualitative case studies of the development and implementation of AI systems. Through a detailed account of the AI development and implementation process, it contributes a better understanding of the project management practices used throughout this process. It provides a detailed understanding of how and to what extent the characteristics of AI drive challenges in the implementation of AI systems, contributing to the strategic perspective of value generation from AI. It also helps explain how certain project management practices can be used to address the challenges arising from AI systems, contributing to the building blocks of future theorizing about AI development and implementation.

Keywords: Artificial intelligence, AI, value from AI, AI development, AI implementation, conceptual research, configurational theorization, qualitative research, case study, literature review, qualitative meta-synthesis.

Research methods: Configurational theorization, qualitative research, case study, literature review, qualitative meta-synthesis.

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List of abbreviations

- AI: Artificial Intelligence
- GenAI: Generative Artificial Intelligence
- ML: Machine Learning
- IS: Information System
- ISBV: Information Systems Business Value
- NLP: Natural Language Processing
- PPE: Personal protective equipment
- HS: Harmonised System
- IT: Information Technology
- CEO: Chief Executive Officer
- EHR: Electronic Health Record
- ED: Emergency Department
- HR: Human Resources
- PoC: Proof of Concept
- MVP: Minimum Viable Product
- SME: Subject Matter Expert
- ISD: Information Systems Development
- RQ: Research Question

To my family.

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Preface

This thesis, authored by Tanya Giannelia, represents original and unpublished research conducted under the guidance of Dr. Ann-Frances Cameron. Earlier versions of all three papers have been presented at conferences as follows:

1) A version of Essay 1 was presented at the Americas Conference on Information Systems (AMCIS) in August 2025.
2) A preliminary version of Essay 2 was presented at the Americas Conference on Information Systems (AMCIS) in August 2022.
3) A presentation of the idea (TREO talk) behind Essay 3 was made at the International Conference on Information Systems (ICIS) in December 2022.

Introduction

We are living in an age of rapid technological development, with artificial intelligence (AI) being one of the significant areas of advancement. In this thesis, AI is defined as "*the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems*" (Berente *et al.*, 2021 : 1435). This constantly moving frontier currently focuses on data-driven prediction and decision making using autonomous computer programs which often involve machine learning, with more recent developments on this frontier being generative AI (GenAI) and agentic AI. AI is found at the intersection of computer science and mathematics, but current progress in the discipline has generated considerable interest in commercial applications of AI. Several factors are driving current progress in AI, including advances in mathematical techniques, increased availability of data, increased computing power coupled with decreased cost of hardware, and availability of cloud-based services that can both store data and run AI systems (Brynjolfsson et McAfee, 2017; Collins *et al.*, 2021). In recent years, uses for AI have grown significantly. AI is being used in finance, software development, customer service, human resources, education, and healthcare, to name a few (Jones, Karamouzis et Sallam, 2025).

Interest in AI continues to grow. Organizational leaders feel that AI increases their competitivity and their ability to take advantage of new opportunities (Ransbotham *et al.*, 2021). According to the Gartner 2025 CEO Survey, 62% of CEOs believe that AI will define the next business era, and that it is the technology that will have the most significant impact in their industries over the next three years (Furlonger *et al.*, 2025). 77% of businesses believe that AI will be one of the three biggest game changers for their industry (Norrie et Davis, 2020). The 2024 Gartner CIO and Technology Executive Survey found that 73% of surveyed CIOs and technology leaders were planning to increase their AI investments (Brethenoux et Yan, 2024).

Despite this growing interest, gaining value from AI is not always easy. In the early days of the current wave of AI progress, only a few organizations reported substantial value generation from their AI investments (Ransbotham *et al.*, 2021). Many organizations still struggle to distinguish between the hype and the reality of AI-based solutions (Mullen et Ramos, 2025). To gain value from AI, organizations require both a strategic vision and appropriate project management approaches to developing and implementing these systems. Against the backdrop of the promises of AI and the potential opportunities for AI to generate organizational value, coupled with the difficulties faced by organizations when attempting to integrate AI systems, the overall research question of this thesis is *How do organizations gain value from AI?*

To understand how organizations can gain value from AI, prior research suggests the importance of both a strategic perspective and appropriate project management practices. To understand the role of the strategic perspective, we can draw on the IS literature on Information Systems Business Value (ISBV) (e.g., Schryen, 2013). This perspective, based on the Resource-Based View (Barney, 1991), examines how IT resources – or IT enabled resources – contribute to organizational value (e.g., Bharadwaj, 2000; Wade et Hulland, 2004). According to this perspective, the fit between IT resources and organizational resources has the potential to generate value for organizations by improving organizational processes and increasing customer value and organizational performance (Davern et Kauffman, 2000; Gellweiler et Krishnamurthi, 2022; Schryen, 2013; Schweikl et Obermaier, 2023). This research also notes that organizational factors such as culture and governance, as well as external industry and country-level factors, can also influence an organization's ability to gain value from it's IS investments (Melville, Kraemer et Gurbaxani, 2004; Schryen, 2013). When planning an information system implementation, organizations also benefit from a strategic vision, a clear understanding on the part of organizational leadership of potential return on investment, top management support, and appropriate change management (e.g., Kloppenborg et Tesch, 2015; Lee *et al.*, 2023; Liang *et al.*, 2007).

Gaining value from AI also depends on appropriate project management practices. Many AI development and implementation initiatives are framed as projects, and effective management of these projects contributes to their value generation potential. Existing research on the development of information systems and digital technologies provides insight into the development practices that can help or hinder value generation from AI-based systems. For example, research consistently shows that projects that use team-based iterative development approaches that include frequent opportunities for customer feedback (Schwaber et Beedle, 2003) are more likely to succeed (Digital.ai, 2022). There are often several phases to the implementation of an IS, from initiation through adoption to assimilation or infusion (Liang *et al.*, 2007; Lyytinen et Damsgaard, 2011). Through this process, organizations must anticipate and manage many challenges, both technical and human, such as being able to anticipate and respond to resistance to information systems (Rivard et Lapointe, 2012).

While previous research on how both the strategic perspective and project management practices contribute to our understanding of an organization's ability to gain value from IS, the applicability of this research to AI-based systems may be limited, in part due to the distinguishing characteristics of these systems. Established IS theories, such as the ISBV framework, may not directly apply to value generation from AI-based systems. The components of GenAI systems (Hosanagar et Krishnan, 2024), for example, may be individually or collectively linked to their value-generation potential, prompting the need to examine them individually and holistically from a strategic perspective. The project management practices that contribute to the success of AI development are also not well understood. Research has begun to examine how software development approaches have evolved to ensure their appropriateness for AI-based systems (e.g., Kreuzberger, Kühl et Hirschl, 2023; Vial *et al.*, 2023). However, because AI systems are developed using advanced statistical and mathematical approaches rather than deterministic code, the composition of AI development teams differs from that of traditional software development (Vial *et al.*, 2023). These differences may prompt different practices to manage the project team than those of traditional software development teams. Furthermore, the way teams developing AI systems work together is not fully understood, particularly in complex environments and under tight deadlines. Finally, while extensive research has been conducted on IS implementation, the project management practices used to address challenges arising from the characteristics of AI are less well understood. For example, the output of an AI system that processes changing data in real time can be unpredictable nature. This unpredictability can impact end-users' ability to effectively use the system (Sturm *et al.*, 2021) and may impact the organization in unpredictable ways. It also means that these systems must be constantly monitored throughout implementation and beyond to ensure they continue to meet their objectives. As the distinguishing characteristics of AI systems may have an impact on both strategic management of these systems and project management practices for their development and implementation, the next section explains the distinguishing characteristics of AI systems in detail.

Distinguishing characteristics of AI systems

There are several characteristics of AI systems that distinguish them from the types of information systems that existing research on value generation from IT is based on. The first characteristic is their reliance on data. AI systems are **dependent on data** to learn and operate. The probabilistic algorithms at the core of AI-based systems require extensive amounts of data both to learn and to operate (Weber *et al.*, 2023). In a recent report, one third of AI leaders indicated that limited data availability or quality was a barrier to AI implementation (Tamersoy *et al.*, 2025). Problems resulting from low data quality during training or from data or model drift during operations include the propagation of biases (van den Broek, Sergeeva et Huysman, 2021) and hallucinations (Huang *et al.*, 2025). These problems can undermine the public's confidence and negatively affect an organization's reputation (Olafsrud, 2025). Poorly combining data from multiple sources can impact its quality and usefulness for data-dependent AI systems (Rinta-Kahila *et al.*, 2022; Singer *et al.*, 2022). Because poor data quality can impact a firm's ability to gain value from its AI investments (Weber *et al.*, 2023), organizations must think strategically about data access and quality (Cai et Zhu, 2015; Davenport, Hoerl et Redman, 2025; Priestley, O'donnell et Simperl, 2023; Vial *et al.*, 2021), and adopt appropriate practices for managing the data used for training their AI systems and during operations (Davenport *et al.*, 2025; Priestley *et al.*, 2023).

Second, AI systems are often described as being **inscrutable**: they are difficult or impossible to audit, even for their developers; the way they operate is not always explainable; the techniques and training data used to develop them are not always transparently shared with clients or users; and their output is not always easily interpretable by the end user (Asatiani *et al.*, 2021; Berente *et al.*, 2021; Burrell, 2016; Marabelli, Newell et Handunge, 2021; Reis *et al.*, 2020; Schuetz et Venkatesh, 2020; Zhang *et al.*, 2021). Inscrutability can impact the potential for an AI system to generate value in many ways. It is often difficult or impossible for developers to audit AI systems, meaning that when the system makes errors or does not operate as intended, developers may not be able to detect the source of the problem, and therefore they may not know how to respond (Burrell, 2016). When users do not understand or cannot interpret a system's output, they may be more reluctant to use it (e.g., Strich, Mayer et Fiedler, 2021; van den Broek *et al.*, 2021; Von Eschenbach, 2021). Certain contexts require AI systems to be explainable, such as in health care (Sendak, Elish*, et al.*, 2020), and in certain jurisdictions, explainability is required by law (van den Broek *et al.*, 2021). There are technical approaches that can increase the explainability of AI systems (e.g., Coussement *et al.*, 2024; Ding *et al.*, 2022), but they may not be sufficient to meet organizations' needs.

A third distinguishing characteristic of AI systems is the **development approach.** The series, sequence and nature of steps used in the development of AI-based systems differs from those used in traditional computer programming (Vial *et al.*, 2023). Computer programing involves writing explicit code and once debugged, this code remains relatively stable. For AI, an algorithmic model is developed using a given data set and fine-tuned to a context. This algorithm learns from examples provided in training data and then is deployed using live data (Asatiani *et al.*, 2020;

Borges *et al.*, 2021; Brynjolfsson *et al.*, 2017; Hosanagar *et al.*, 2024). Characteristics of the AI workflow include major feedback loops, sequential dependencies (i.e., the next step to be completed depends on the data outputs from a previous step), and an indeterminate number of cycles of data exploration and model experimentation (Amershi *et al.*, 2019; Vial *et al.*, 2023), suggesting that developing these systems often requires a different approach that is neither strictly agile nor strictly traditional (Vial *et al.*, 2023).

Not only does development process and approach of AI systems differ, the **composition and the management of AI project teams** may also differ from that of traditional software development teams. AI development requires people with training in mathematics and statistics, and specialized skills to develop and train the algorithms, such as data scientists and machine learning engineers (Chandrasekaran et Linden, 2020; Vaast et Pinsonneault, 2021). Employees with these skills and expertise must be integrated into development teams (Blok, Trudeau et Cassidy, 2021), yet many organizations report that their employees have insufficient understanding and training on AI (Ransbotham *et al.*, 2021), limiting their ability to contribute effectively to AI development and implementation projects. Furthermore, organizational employees involved in operating AI systems or using their output often require a minimum level of AI literacy to be effective in their roles (den Hamer *et al.*, 2024). As AI techniques and approaches evolve rapidly, the specific skillsets required by both technical and non-technical employees is also evolving.

A three-essay approach

As the above paragraphs demonstrate, while previous research can inform some aspects of how organizations can gain value from AI, there is still much that is not understood. From a strategic perspective, the ISBV literature explains why it is important for there to be a fit among organizational resources and factors and information technologies, but exactly how AI technologies – and their components – fit with organizational resources and other organizational factors is less clear. Literature on information systems development and on implementation of information system offers suggestions of how project management practices can support the teams developing information systems, but less is known about how these practices apply to AI development teams. This literature also offers suggestions of how to ensure smooth integration of a new system into an organization, but when the system is inscrutable and its output – and therefore impact on the organization – is unpredictable, these suggestions may not apply.

To address the need to better understand how organizations gain value from AI, this thesis uses three essays (see **Table O-1**). The first essay examines how this complex technology can be best aligned with organizational strategy to gain value. It does so within the unique setting of religious organizations. It conceptually explores how the components of generative AI (a specific type of AI) and the layers of religious authority (an element of organizational strategy for religious organizations) need to fit together to allow religious organizations to generate religious value from generative AI. The second essay aims to inform understanding of how development teams manage the development of AI system in the context of a complex ecosystem and a situation requiring rapid development and implementation. It studies the rapid design, development, and initial implementation of an AI-based system to shed light on how organizations can more rapidly gain value from their AI projects. The third essay explores if and how the characteristics of AI influence development and implementation of AI. Through a meta-synthesis of published case studies, it explores how organizations manage the development and implementation of AI systems, highlighting the ways the characteristics of AI impact development, implementation and use of these systems and the project management practices that organizations employ to respond to these impacts.

Organization of the thesis

Essay #1 is a conceptual paper that examines value generation from AI in a non-traditional setting. It presents a theoretical explanation of how religious organizations can gain religious value from generative AI through the alignment of the components of generative AI (Hosanagar *et al.*, 2024) with the layers of religious authority (Campbell, 2007), using the IS business value (ISBV) framework (Schryen, 2013) as a conceptual foundation. According to the ISBV framework, a fit between IT resources, non-IT resources, and other organizational and external factors influences an organization's ability to gain value from its IT investments. This essay focuses on the fit between IT resources, modeled as the components of generative AI (Hosanagar *et al.*, 2024), and an organizational factor, modeled as religious authority and examined at the level of layers of religious authority (Campbell, 2007; Cheong, 2021). Religious organizational value is conceptualized as both the number of adherents to a religious organization and increasing the depth of their commitment (Miller, 2002). This essay proposes a configurational perspective to fit (Venkatraman, 1989) among components of GenAI and layers of religious authority. It concludes with an agenda for future research. It presents how the components of GenAI must be configured according to the relative importance of each layer of religious authority for a GenAI system to be able to generate religious value for a religious organization.

The first essay contributes primarily to the strategic perspective of value generation from AI, as understanding the role fit between IT resources (components of GenAI) and organizational factors (layers of religious authority) is a strategic question. It makes five contributions. First, it contributes a better understanding of religious value creation and performance of religious organizations when using digital technologies. While extant research has examined performance of religious organizations in general, this study theorizes how digital technologies can contribute to religious value generation for these organizations and to their performance. Second, it extends the application of the ISBV framework to the context of religious organizations. A better understanding of the applicability of this framework to different contexts and different conceptualizations of value is an important building block for future theorization (Whetten, 1989). The third contribution is a detailed examination of one organizational factor – religious authority – in the generation of ISBV. This detailed examination helps to clarify the potential role of organizational factors in ISBV. The fourth contribution is to the growing literature that uses configurational theories to understand business value generation from IS. By proposing a configurational, rather than a pairwise or moderation-type fit to ISBV, this study sheds light on the mechanisms by which different factors and resources contribute to value from IS. The fifth contribution is a demonstration of the feasibility and impact of disaggregating the IT construct in the ISBV framework, paving the way for future research to examine this and other constructs in a more fine-grained manner.

Essay #2 is a single case study that examines the rapid development and implementation of a complex project involving AI and provides insight into how organizations can accelerate value generation from AI. This essay studies the development and initial implementation of "AISys," an AI-based information system that was successfully developed in the early months of the COVID-19 pandemic to fast-track medical supplies and personal protective equipment. Data sources include interviews and project documentation collected from both the client and the supplier. Following an analytic induction approach (Patton, 2002), a theoretical framework based on the transactional model of stress (Lazarus et Folkman, 1984) and adapted to the project team level of analysis (Liu et Liu, 2018) was developed to guide the data coding and analysis. This paper allowed for a better understanding of how the project team was able to cope with project stressors to successfully complete the project.

The second essay contributes primarily to a better understanding of the project management practices linked to value generation from AI. Through a detailed examination of one AI project, this essay offers three key practices for managing AI projects and explains how each of these practices contributes to the successful management of rapid AI projects in complex ecosystems. The first practice is the use of socialization, or specific actions intended to modify the behavior of other organizations, and how it can benefit multi-organizational AI projects. The propositions arising from this section are about the importance of socialization activities among all actors in the ecosystem involved in the project. The second practice is the role of strategic overstaffing of data science experts – in particular retaining experts familiar with the project and the environment within the "orbit" of a project, available to assist if needed – in accelerating AI projects in complex environments. The proposition arising from this section are about the role of "retaining in orbit", practiced by some data science staff. The third practice is conducting strategic data assessment blueprinting for organizations wanting to carry out a portfolio of AI projects. In this study, these practices apply directly to inter-organizational AI development and implementation projects in complex environments and contexts requiring rapid execution but may also apply more broadly to AI development and implementation in other contexts. The proposition arising from this study is about the role of strategic data assessment blueprinting for developing a portfolio of projects.

Essay #3 is a meta-synthesis of qualitative case studies (Hoon, 2013) that focuses on how organizations manage the development and implementation of AI-based systems. Successful implementation is necessary for organizations to gain value from their investments in AI-based systems. As AI-based systems are at a constantly moving frontier of technological advancements (Berente *et al.*, 2021), there may be challenges specific to these systems, and specific practices required to address these challenges. Through an examination of 12 cases of AI implementation across contexts, this essay uncovers how the distinguishing characteristics of AI systems influence their development and implementation, and how organizations navigate the implementation of AI-based systems to generate value from them.

The third essay contributes to both the strategic perspective and the project management practices related to generating value from AI. First, this essay offers a detailed account of the AI development and implementation process, derived from a synthesis of 12 case studies, contributing to a better understanding of the project management practices used throughout this process. The insights derived from this synthesis provide empirical grounding for future theorization on the management of the development and implementation of AI systems. Second, it provides a detailed understanding of how and to what extent the characteristics of AI drive challenges in the development and implementation of AI systems, contributing to the strategic perspective of value generation from AI. Third, this essay provides both empirical evidence and theoretical arguments to explain how certain project management practices can be used to address the challenges arising from AI systems, contributing to the building blocks (Shepherd et Suddaby, 2017) of future theorizing about AI development and implementation.

Table 0-1 Organization of the Thesis

Essay	**Essay 1**	**Essay 2**	**Essay 3**
Title	Generating Religious Value from Generative AI: A Contingency Fit Perspective	Managing AI Within a Complex Supply Chain Ecosystem: The AISys Project at CityPort	How Organizations Navigate AI Implementation: An Interdisciplinary Qualitative Meta-Synthesis of Case Studies
Organization	Religious organizations	Supply chain ecosystem	Various types of organizations
Value	• Non-monetary value • Religious value and performance of religious organizations	• Value for multiple stakeholders • Rapidly gaining value	• Different types of value for organizations and individuals
AI	Generative AI	Natural Language Processing	Varied, primarily ML
Method	Conceptual	Qualitative single case study	Meta-synthesis (literature review) of published qualitative case studies
Contributions	• Contributes to a better understanding of religious value creation and performance of religious organizations when using digital technologies • Extends the ISBV framework to the context of religious organizations • Provides a detailed examination of an organizational factor – religious authority – in the generation of ISBV • Contributes to the growing literature that uses configurational theories to understand business value generation from IS • Demonstrates the feasibility and impact of disaggregating the IT construct in the ISBV framework.	• Brings to light how socialization, or specific actions intended to modify the behavior of other organizations, can be beneficial for multi-organizational AI projects. • Suggests that strategic overstaffing of data science experts can help accelerate an AI project in a complex environment. • Suggests that organizations wanting to carry out a portfolio of AI projects should consider engaging in strategic data assessment blueprinting.	• Through an interdisciplinary review, uncovers the multiple ways AI system development and implementation is managed, across contexts and industries. • Uncovers how and to what extent the implementation of these systems differs from other types of information systems by identifying the impact the distinguishing characteristics of AI has on AI system development and implementation. • Provides theoretical arguments and empirical evidence of how certain tactics of an organization can manage challenges that arise from the distinguishing characteristics of AI systems.
Previous presentations	Presented at AMCIS 2025 (Complete paper).	Preliminary version presented at AMCIS 2022 (ERF).	Preliminary idea presented at ICIS 2022 (TREO)

Chapter 1
Generating Religious Value from Generative AI: A Configurational Fit Perspective

Abstract

This conceptual essay presents a configurational theory that explains how religious organizations may generate religious value from generative AI (GenAI). We draw on IS Business Value (ISBV) literature for a framework of value generation from IT, and literature on religion and new media for an understanding of factors influencing adoption and value generation from IT in religious organizations. This conceptual paper seeks to address the research question "How does religious authority influence value generation from generative AI by religious organizations?" Previous research suggests that religious authority influences how religious leaders and adherents use IT for religious purposes. Using the ISBV framework as a theoretical lens, we propose a configurational approach to the alignment between layers of religious authority and the components of GenAI and propose that this alignment influences the ability of religious organizations to generate religious value from GenAI. This paper contributes to the understanding of religious value generation from information systems for religious organizations; it demonstrates the applicability of the ISBV framework to alternative conceptualizations of value by presenting an extension of the framework to the context of religious organizations; it extends research on the role of organizational factors in the generation of ISBV by examining one specific organizational factor relevant to religious organizations; it contributes to ongoing work exploring the configurational nature of ISBV; and it demonstrates the benefit of disaggregating the IT resources construct by examining the components of GenAI. We conclude with an agenda for future research.

1.1 Introduction

In the fall of 2024, St. Peter's Church in Lucerne, Switzerland, implemented an interesting technological upgrade: between August and October 2024, an artificial intelligence (AI)-powered chatbot represented as a hologram of Jesus was installed in a confessional. With the push of a button, worshipers could speak their concerns, ask questions and get a response or advice in accordance with the Catholic faith. As is common in confessionals, the hologram was located behind a screen and only minimally visible to participants. The bot, created by researchers in computer science and theology at the Lucerne University of Applied Sciences and Arts, was presented as an experiment to visitors, not as a replacement of clergy. Nonetheless, two thirds of visitors found interacting with the bot provided them with a "spiritual experience"[1].

This is far from the first instance of religious use of generative AI (GenAI). Not long after ChatGPT – a multi-purpose GenAI chatbot – was released to the public, religious adaptations of the chatbot began appearing. GitaGPT.org provides answers based on a Hindu text, the Bhagavad Gita. HadithGPT.com is a GenAI chatbot trained on over 40,000 Hadiths, or Islamic teachings. KhalsaGPT.net is a Sikh GenAI chatbot, Kosher.chat is a Jewish GenAI chatbot, and Magisterium.com is a Catholic GenAI system. Not only are individuals using these systems; religious organizations are also considering how they could benefit from GenAI. Religious leaders are experimenting with GenAI to write sermons, or to conduct research to provide religious advice[2]. Further examples of how GenAI could be used by religious organizations to increase the efficiency of religious processes, and gain value from GenAI, include: a group of Catholic priests who used it to compile feedback from priests participating in a Synod[3], and Iranian clerics who used it to help issue fatwahs[4].

GenAI tools are a category of computer programs that use neural networks based on deep learning to generate new content, such as text, images, music, or computer code (Feuerriegel *et al.*, 2024). GenAI can be used by organizations for different purposes and in different contexts, and value can be gained through improving the efficiency or effectiveness of existing organizational processes, or by offering novel opportunities for value generation. This conceptual paper focuses on GenAI systems that are used by religious organizations for religious purposes. These systems include written text and audio content, and the corresponding design of the visual or audio interface.

Many types of organizations use GenAI to obtain value. However, religious organizations have distinct characteristics which may require additional consideration to understand how they are able to generate value from GenAI, including the presence of a religious authority structure, the type of value they generate and the way performance is defined and measured (Chaves, 1993; Miller, 2002). Religious organizations can be defined as social enterprises whose legitimacy is in

[1] https://www.theguardian.com/technology/2024/nov/21/deus-in-machina-swiss-church-installs-ai-powered-jesus
[2] https://www.theguardian.com/technology/2023/apr/07/chatgpt-artificial-intelligence-religion-faith-leaders
[3] https://www.pillarcatholic.com/p/how-ai-helped-shape-asias-synod-document
[4] https://www.middleeastmonitor.com/20230925-irans-clerics-look-to-harness-ai-to-issue-fatwas-more-efficiently/

whole or in part determined by a supernaturally- or spiritually-based authority structure, and whose primary purpose is to create, maintain and exchange supernaturally- or spiritually-based rewards and compensators (Chaves, 1993; Miller, 2002; Stark et Bainbridge, 1980). This definition recognizes the centrality of the religious authority structure in religious organizations. The layers of religious authority are ideology, community structures, leadership, and texts. Religious authority has been shown to influence the perception and use of various technologies by religious organizations (Campbell, 2007; Cheong, 2021).

Some religious organizations – like other types of organizations – may use GenAI to optimize the performance of "back office" operations like building maintenance or fundraising activities, performance and value can be measured financially. Religious performance, however, is measured in terms of how well a religious organization recruits and retains adherents and increases the depth of their religious commitment (Miller, 2002). Religious organizations offer value to their adherents through unique combinations of rewards and compensators (Boggs et Fields, 2010; Miller, 2002; Stark *et al.*, 1980; Tracey, 2012). The examples above of religious versions of GenAI models demonstrate the growing prevalence of the use of GenAI for religious purposes, indicating that this technology can generate religious value by supporting a religious or spiritual experience. However, not all uses of GenAI seem to generate religious value: some instances of using GenAI to gain religious value are deemed promising[5] whereas others are considered problematic[6]. It is thus important to understand what might be driving these differences.

While there is literature on the intersection of religion and digital technology, it does not specifically address religious organizational value creation, nor does it address GenAI and religion. Computer science studies report individual spiritual or religious experiences when interacting with religious digital devices (e.g., Asante-Agyei, Xiao et Xiao, 2022; Trovato *et al.*, 2019). The literature on digital religion in both communication and religious studies explores how digital technology is used to communicate religion, and how religious organizations and adherents shape digital technology to fit their beliefs (Campbell, 2007; Cheong, 2021; Hutchings, 2017). Research has also examined how digital technology and religious authority are mutually challenged and influenced (Campbell, 2007; Cheong, 2021): for example, religious-social shaping of technology refers to the process by which religious organizations shape digital technologies to match their belief system (Campbell, 2010). Though extensive, this literature has not examined

[5] https://www.middleeastmonitor.com/20230925-irans-clerics-look-to-harness-ai-to-issue-fatwas-more-efficiently/
[6] https://www.tmatt.net/columns/2024/4/30/the-ai-rise-and-fall-of-father-justin-is-a-technology-parable-for-our-time

the connection between religious authority and value generation from IT, nor has it examined GenAI in detail.

In strategic management of IT literature, IT resources are often aggregated or black-boxed (Schryen, 2013). However, there may be technological challenges specific to developing and deploying religious text-based GenAI. Generic large language models (LLMs), the foundational technology of GenAI applications, were designed as general-purpose technologies. These models were trained on vast sets of texts so their output would appear natural, but because they were not explicitly trained on context-specific data, they often provide incorrect but seemingly confident answers (called "hallucination") (Huang *et al.*, 2025). For some religious organizations, like the Catholic Church, being in possession of a single truth is critical (McGreavy, 2022), making hallucinations likely problematic. Developing an LLM from scratch can be costly, therefore most organizations opt for tailoring or fine-tuning existing models (Hosanagar *et al.*, 2024). While different approaches can be adopted to tailor a generic model, their ability to reliably generate religious value may depend on specific aspects of a religious organization, such as religious authority.

Most literature exploring the intersection of IT and religion looks at design or use of IT for religious purposes (Campbell, 2007; Cheong, 2021), but not at the generation of value from IT for religious organizations. Furthermore, while literature has begun to explore religion and GenAI, an overarching understanding of religious value generation from GenAI has yet to be demonstrated. Thus, what remains underexplored is how religious authority dimensions influence how religious organizations can gain value from IT in general, and from GenAI specifically. Therefore, this conceptual paper seeks to address the research question "*How does religious authority influence value generation from generative AI for religious organizations*?"

One way to understand value generation from GenAI is through the contingency perspective exemplified in the IS business value (ISBV) literature (Schryen, 2013). According to this perspective, value generation from IS is contingent on a fit between IS and non-IS resources, and the moderating influences of other internal and external factors such as organization size and governance and market turbulence or industry (Melville *et al.*, 2004; Sabherwal et Jeyaraj, 2015; Schryen, 2013). Previous research in this area has noted that IS generates value primarily through business process improvements enabled by IS, that in turn can increase productivity or affect other measures of organizational performance (Davern *et al.*, 2000; Schryen, 2013). In this conceptual paper, we use the ISBV framework (Schryen, 2013) as a theoretical lens to propose a configurational theory of potential for religious value generation using GenAI. Recognizing the centrality of the authority structure for religious organizations (Chaves, 1993) and answering the call to disaggregate the IS resources construct in the ISBV model and to explore contextual factors in the ISBV framework (Schryen, 2013), we examine how the alignment between layers of religious authority and the components of GenAI influences the ability of religious organizations to generate religious value from generative AI.

This paper makes five main contributions. First, we contribute to the understanding of religious value generation from information systems for religious organizations. Second, we demonstrate the applicability of the ISBV framework to alternative conceptualizations of value by presenting an extension of the framework to the context of religious organizations. Third, we extend research on the role of organizational factors in the generation of ISBV by examining one specific organizational factor relevant to religious organizations. Fourth, we contribute to ongoing work exploring the configurational nature of ISBV. Fifth, we demonstrate the benefit of disaggregating the IT resources construct by examining the components of GenAI.

In the next section we will review the literature on religious value generation and religious authority, ISBV, and the components of GenAI. Then we will present a configurational theory of the role of religious authority dimensions in the generation of value from GenAI by religious organizations. We conclude with a discussion of our contributions and a presentation of directions for future research.

1.2 Literature Review and Theoretical Background

1.2.1 Background on Religious Organizations

Religious organizations share many characteristics with non-religious organizations, but here we will focus on the characteristics that distinguish religious organizations from other types of organizations, and that may influence value generation. We begin by examining the belief system of the religious organization, as it plays a role in determining the potential value for adherents. A religious belief system is defined here as a *structured set of tenets or principles that a religious group or organization holds to be true. Elements of a belief system include morality and values, empirical reality, life purpose, prescriptions and proscriptions of behavior, and other substantive beliefs of the religious organization* (Usó-Doménech et Nescolarde-Selva, 2016). The belief system is unique to each religious organization and is instantiated in the specific rewards and compensators an adherent can obtain through participation in the religious organization. Like all organizations, religious organizations must ensure their financial viability. In addition, the survival and growth of religious organizations depends on adherents belonging to them and following their belief system (Miller, 2002).

Value for adherents can be conceptualized as the rewards and compensators they receive through participation in religious organizations (Adria, 2024; Miller, 2002). Examples of rewards include participation in church services, social activities, education and socialization of children. Similar benefits can be obtained through other means, and as such, rewards are not unique to religious organizations (Miller, 2002). Compensators, on the other hand, are uniquely provided by religious organizations. Defined as "*postulations of reward according to explanations that are not readily susceptible to unambiguous evaluation*" (Stark & Bainbridge, 1980: 121), compensators are tied to the religious or spiritual experiences that can be obtained by participating in a religious organization. Examples of compensators a religious organization may offer include religious doctrines, including belief in an afterlife; religious experiences, such as visions or speaking in tongues; private devotionalism and prayer, as a mechanism for obtaining divine guidance or comfort; and a sense of moral superiority, or the comfort of being chosen by the divine (Riesebrodt et Konieczny, 2009; Stark *et al.*, 1980).

Disentangling sources and recipients of religious value, and their relationship with religious organizational performance can be complicated. According to strategic management literature, an organization's value chain can be separated into discrete categories such as suppliers, buyers and internal production (Porter, 1985). In many religious organizations, however, the adherents are simultaneously consumers and producers of religious value. The "product line" of religious organizations is the combination of rewards and compensators they offer, but examples of rewards and compensators include membership in a community, and socialization of children – which are only possible through the participation of adherents in the religious organization (Miller, 2002). Value for individual adherents is instantiated in the benefits received from the rewards and compensators conferred through participating in the religious organization. Value for organizations on the other hand can be measured through the number of adherents and the depth of their commitment to its belief system (Miller, 2002; Tracey, 2012).

Rewards and compensators can be delivered to individuals via religious processes, for example pilgrimages, religious education or religious counsel (Boggs *et al.*, 2010; Turner et Nasir, 2016). Religious organizations also engage in organizational processes, such as performing religious ceremonies, allocating organizational resources and strategic planning. As in other types of organizations, process performance can be measured in terms of efficiency and effectiveness. It is important to note that in some cases and in some religious organizations, an objective of a religious process may be the suffering or toil it entails, indicating that increased efficiency is not always the goal of religious process improvement. An example of this would be religious pilgrimages, where the journey is as important as the destination (Imanda *et al.*, 2017). When examining religious process performance, outcomes related to effectiveness may be more appropriate than those related to efficiency.

1.2.2 Religious Authority Structure and Layers of Religious Authority

Beyond rewards and compensators, another attribute of a religious organization's belief system – which is also a way religious organizations vary and are distinct from other types of organizations – is its religious authority structure. A religious authority structure "*attempts to enforce [the] order [of a religious organization] and reach its ends by controlling the access of individuals to some desired good, where the legitimation of that control includes some supernatural component*" (Chaves, 1993, p. 193). The religious authority structure determines right and wrong, or acceptable and unacceptable, within a religious organization. The four dimensions or "layers" of religious authority are text, ideology, community structure and leadership (Campbell, 2007; Gifford, 2005; Weber, 1947). These layers are likely present in all religious organizations (Gifford, 2005). What varies among organizations is the relative importance of each layer within each religious organization (Campbell, 2007; Cheong, Huang et Poon, 2011; Gifford, 2005; Weber, 1947). In reality, layers of authority are intertwined and mutually influence each other (Gifford, 2005). However, for analytic purposes, we examine each layer individually. Each are illustrated with examples from selected religious organizations.

First, religious **texts** refer to the recognized and codified teachings or official documents of a religious organization. Authority from text refers to the extent to which religious authority comes from a specific bounded collection of texts. For example, for Muslims, the Quran – the sacred scripture – and the Hadiths – records of the teachings of the prophet Mohammed – provide the foundation of Islamic law (Campbell, 2007; Gifford, 2005). In Judaism, the study of religious texts (the Torah and the Talmud). This study involves learning Hebrew, the language in which Jewish texts were originally written, and learning to read and understand the texts, is an important part of religious practice (Campbell, 2007). There are several sacred Hindu scriptures, including the *veda* and the *Bhagavad-gita* (Knott, 1998). Evidence of the authority of the Sikh scripture, the

Adi Granth (sometimes referred to as the Guru Granth Sahib), is evidenced by the fact that the mere presence of the Adi Granth in a room or building transforms that space into a temple or *gurdwara* (Gifford, 2005).

Second, the **ideology** of a religion refers to commonly held ideas of faith, beliefs, or an otherwise shared identity connected to religious beliefs (Cheong, 2021). Authority from ideology refers to the extent to which religious authority comes from the commonly held beliefs and ideas of faith of adherents of a religion. Central to Sikhism is the belief that one's destiny is influenced by one's past and future lives, a concept often referred to as karma. This belief governs behavior in Sikhism (Jakobsh, 2012). The importance of adherence to the Muslim "straight path" is an example of authority from ideology (Campbell, 2007; Lawrence, 2002).

Third, religious **community structure** refers to the structures present within a religious organization, how the community worships, what practices are followed, how the community stays connected and how the community creates and maintains systems, traditions and discourses (Campbell, 2007). Authority from structure refers to the extent to which religious authority comes from community structures or groups. For example, in Sikhism, authority lies in the sacred texts (as mentioned above) but also in the Panth, or the community of Sikhs (Gifford, 2005). In Judaism, certain systems and discourses created and maintained by the Jewish community govern behavior in this religion (Campbell, 2007).

Finally, religious **roles** or leadership refer to the recognized religious leaders within a religion. Different religious organizations determine who occupies leadership roles in different ways. For example, leaders may be incarnated, like the Dalai Lama; trained, like a Jewish rabbi; or receive a divine calling, like some shamans (Cunningham, 2006). Authority from roles or leadership refers to the extent to which religious leaders are perceived as authoritative interpreters and disseminators of religious knowledge and practice (Campbell, 2007; Cheong *et al.*, 2011). For example, Hindu gurus are sought out for the wisdom they can impart (Knott, 1998). In Catholicism, the pope holds primary religious authority, with bishops and priests also recognized as authority figures (McGreavy, 2022).

1.2.3 IS Business Value

To understand how religious organizations generate value from GenAI, we draw on the literature on IS business value (ISBV). ISBV is defined as "*the impact of investments in particular IS assets on the multidimensional performance and capabilities of economic entities at various levels,* *complemented by the ultimate meaning of performance in the economic environment*" (Schryen, 2013: 141). "IS assets" refer to all types of investments in IS, including hardware, software, IT personnel and IT management(Melville *et al.*, 2004). Early literature on ISBV aggregated IS investments (e.g., Bharadwaj, 2000; Melville et al., 2004), but later studies argue for disaggregation (e.g., Schryen 2013). "Multidimensional performance" refers to the different categories of value generated by IS, including market value, shareholder value, accounting performance, consumer surplus, productivity and capacity utilization, with specific measurements for each (e.g., Brynjolfsson et Hitt, 2003; Brynjolfsson, Hitt et Yang, 2002; Gellweiler *et al.*, 2022). The "various levels" refer to performance of business processes, organizational performance, or customer value (Davern *et al.*, 2000; Gellweiler *et al.*, 2022; Sabherwal *et al.*, 2015; Schryen, 2013). Some research suggests that IS impacts organizational value by first improving business processes (e.g., Bardhan, Krishnan et Lin, 2013; Davern *et al.*, 2000; Schweikl *et al.*, 2023; Tallon, 2007). Other studies suggest ISBV research should focus on the perception of value by specific stakeholders (Schryen, 2013), such as customer value (Gellweiler *et al.*, 2022). The "ultimate meaning of performance" refers to the fact that performance is measured by what the firm can accomplish with the gains obtained through IS. Business process performance can be conceptualized as efficiency and effectiveness. Examples of gains include improved process efficiency, the ability to offer new products or services, or to offer these products and services in different ways (Melville *et al.*, 2004; Schryen, 2013).

ISBV research recognizes that investments in IS alone do not generate value for organizations, and that measuring the presence and value of IS investments and resources is not sufficient to explain value generated from IS. Literature has shown that value from IS is contingent on fit or synergies with other factors (Melville *et al.*, 2004; Schryen, 2013; Wade *et al.*, 2004). First, IS resources must fit with non-IS organizational resources, such as non-IT physical assets, non-IT human resources and organizational resources including rules and policies, practices and culture (Melville *et al.*, 2004; Schryen, 2013). Second, additional factors both internal and external to the organization can influence organizational performance. Attributes of organizations that can influence performance include size, structure, governance, and whether an organization is public or private (Roberts, Jeyaraj et Pullin, 2023; Turedi et Zhu, 2019). External factors include industry structure and country level factors. Prior research has noted that organizational factors often have greater explanatory power than industry or country level factors (Melville *et al.*, 2004; Schryen, 2013).

Early studies on ISBV focused on a pair-wise fit (Venkatraman 1989) between IS and non-IS resources, or on the moderation of this pair-wise fit by other organizational factors. Later research notes that fit may be more complex, noting that ISBV may be contingent on multiple elements, and previously aggregated elements must be disaggregated to better understand fit (e.g. Schryen, 2013). This suggests that a configurational approach, examining fit between multiple factors or conditions, may be more appropriate to understanding ISBV. Configurational approaches were first used in organizational research to understand the intertwined influence of multiple factors. Configurational theories posit that it is not individual variables, but an internally coherent set of conditions that lead to an outcome. Configurational approaches are based on the concepts of heterogeneity and causal complexity. Heterogeneity refers to the fact that it is the combination of multiple variables that leads to an outcome, not the predictive strength of each factor individually. Causal complexity means there are likely multiple combinations of factors that lead to an outcome, not a single configuration (Charles C. Ragin, 1987).

In IS, configurational approaches have been used to better understand the contribution of several factors to the creation of ISBV, beyond the pairwise fit of IT resources and non-IT resources. Fink (2011) demonstrates that a configurational approach to examining the contribution of factors to IT competitive value leads to different insights than a direct or mediation approach. Wang et al. (2019) explore how organizations leverage big data analytics to improve care in healthcare organizations by examining the configuration of BDA capabilities, organizational resources and organizational capabilities. Ortiz and Raymond (2022) examine the effect of configuration of IT capabilities, dynamic capabilities and manufacturing context on business performance. Hu et al. (2023) study the effects of configurations among intellectual and social alignment, and organizational and environmental factors on IT-enabled organizational agility. A configuration or "gestalt" model has been proposed to examine fit in ISBV, understanding that IT must "fit" with several organizational factors, such as organizational processes, structures, and culture (Cao, 2010; Cao, Wiengarten et Humphreys, 2011). **Figure 1-1** presents a conceptual overview of ISBV research.

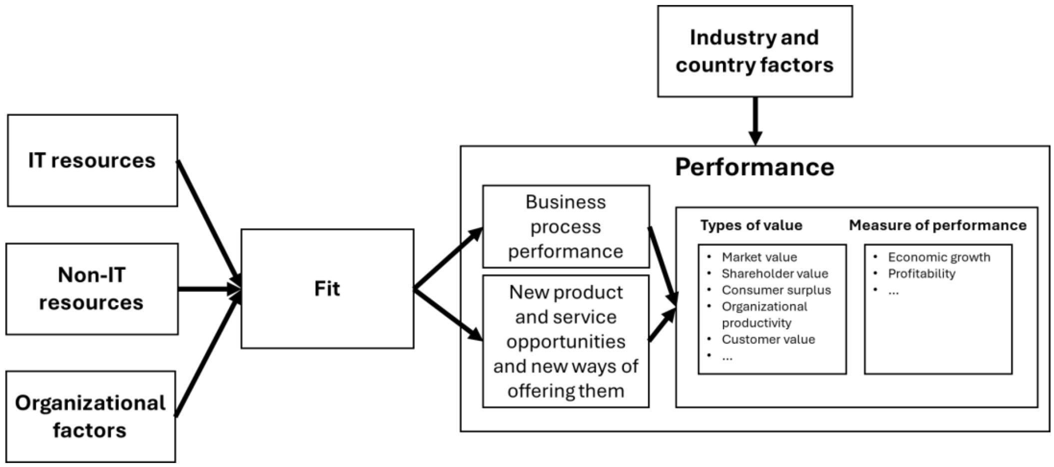

Figure 1-1 Conceptual Overview of IS Business Value Research

1.2.4 Business Value from AI

Widespread commercial application of AI is still in its early stages, meaning that research is lacking on how firms generate business value from AI in general, and from GenAI specifically. However, early research provides some insight. AI-enabled automation can spur improvement and transformation of business processes, resulting in increased process efficiency, which can lead to organizational productivity (Borges *et al.*, 2021; Mikalef *et al.*, 2023). AI can also enable the creation of new or enhanced products and services, providing new opportunities to generate value customer value (Borges *et al.*, 2021; Enholm *et al.*, 2022).

Several factors enable and inhibit organizational value generation from AI. First, AI systems require data. This data must be present, accessible and of sufficient quality (Baier, Jöhren et Seebacher, 2019; Enholm *et al.*, 2022; Ghasemaghaei, 2021; Vial *et al.*, 2021). Attributes of big data include volume, velocity, veracity, variety and value (Mikalef *et al.*, 2018). These attributes can differentially impact organizational ability to generate value from their data. For example, volume may negatively affect the veracity of big data, but velocity and variety can positively impact it (Ghasemaghaei, 2021). If the underlying dataset used to train an AI algorithm is biased, these biases will be reproduced in use (Baier *et al.*, 2019). In addition to data, the organization must have access to sufficient computing power, whether in-house or leased from a cloud services provider. Organizational factors necessary for any technology implementation apply to AI as well, such as top management support, a culture of innovation and organizational readiness. Furthermore, to gain value from AI organizations should have an AI strategy (Mikalef et Gupta, 2021), and ensure their employees trust AI (Makarius *et al.*, 2020). Finally, organizations should pay attention to the ethical and moral aspects of AI, for example by managing and mitigating the impact of biases in training data (Baier *et al.*, 2019; Coombs *et al.*, 2020; Enholm *et al.*, 2022).

Emerging research indicates that the ability of GenAI systems to retrieve and synthesize information influences their potential to create strategic, informational and transactional value for organizations through the transformation of business process management and decision-making (Feuerriegel *et al.*, 2024; Santos Gabriel, 2024). This research seems to indicate that investments in a small set of GenAI techniques applied broadly to several operational situations is more effective than applying a wide variety of techniques to a small set of use cases – particularly in increasing employee productivity (Du *et al.*, 2023). However, to date, limited research has been conducted on value generation from GenAI (Santos Gabriel, 2024), and therefore the exact ways in which GenAI can add value to organizations remain understudied.

As the present study seeks to understand the relationship between the many layers of religious authority and the components of GenAI in generating religious value, we follow Cao et al. (2011) and propose examining the fit between an organizational factor (religious authority) and an IT resource (GenAI). We also propose using a configurational approach and disaggregate both constructs. In the case of the IT resources construct, we propose examining the role of components of GenAI independently and collectively (Charles C. Ragin, 1987; Venkatraman, 1989). Next, we examine the components of GenAI.

1.2.5 The Components of Generative AI

GenAI applications have been designed as general-purpose tools that can be customized and implemented in different ways for specific use cases and organizations. Hosanagar and Krishnan (2024) propose a framework of components of GenAI, to understand the function and value generation potential of each. The components necessary to developing and deploying GenAI systems are computing infrastructure, data, foundation models, the tooling layer and LLM applications (Feuerriegel *et al.*, 2024; Hosanagar *et al.*, 2024).

Computing infrastructure in this framework is defined as the hardware and network infrastructure on which the GenAI apps run. Most GenAI systems, including LLMs, run on cloud infrastructure, but locally deployable models have also been developed.

The current approach to developing GenAI systems is to build on top of a **foundation model** (Feuerrigel et al., 2024). Foundation models are defined as models trained on a broad dataset that can subsequently be adapted for a wide range of tasks (Schneider, Meske et Kuss, 2024). Foundation models provide the framework for a GenAI application to operate. They can be integrated into organizational systems via an API, for example. Most foundation models were developed by industry, according to the interests and priorities of the company that developed them, and for commercial use (Bommasani *et al.*, 2021; Tao *et al.*, 2024). Organizations, including religious organizations, wanting to develop a GenAI system must therefore choose from only a handful of commercially available foundation models developed (Bommasani *et al.*, 2021). Some publicly available foundation models include GPT4o developed by OpenAI and Llama 2 developed by Meta.

Relying on commercially-developed foundation models for religious GenAI systems raises two potential concerns. The first is that the data used to develop foundation models is primarily scraped from the internet, where some languages, cultures and groups are over-represented, some under-represented and some mis-represented (Tao et al. 2024). Therefore, the resulting model, its parameters and output replicate any biases inherent in this foundational data (Bommasani *et al.*, 2021). GenAI systems have been found to exhibit biases towards groups who may be underrepresented or misrepresented in the broad data used to train the foundation model (Guo *et al.*, 2024; Tao *et al.*, 2024). A second concern is model drift, or the tendency of a model to change over time, sometimes dramatically and unexpectedly (Chen, Zaharia et Zou, 2024), requiring constant monitoring (Feuerriegel *et al.*, 2024).

To adapt a foundation model to a specific context, organizations train the model on a curated, contextualized **training dataset**. Using a carefully defined dataset to train a model can help ensure accuracy of the GenAI system's output, or its ability to produce output in line with the needs of the organization deploying it (Huang *et al.*, 2025). Availability and accessibility are important dimensions of the quality of training data (Enholm *et al.*, 2022; Mikalef *et al.*, 2018; Vial *et al.*, 2021). Additionally, for a model to be trained on specific content, the training data must be appropriately formatted (i.e., digitized, tokenized and vectorized) (Lewis *et al.*, 2020).

The **tooling layer** refers to the approach used to fine-tune the model. One technique is retrieval-augmented generation (RAG), an approach which provides the model with specific instructions or code so that it only searches specific sources when generating a response to a query (Lewis et al. 2020). A second approach is to use techniques like online modelling, which refers to augmenting a model with the capability to retrieve information in real time (Feuerriegel *et al.*, 2024). A third approach is to retrain the neural network of the foundation model using domain-specific data (Hosanagar *et al.*, 2024).

The final component of GenAI systems is the **LLM application**, or what the user uses to interact with the GenAI system. It includes the website or app used to access the GenAI system and all design components of the interface, including the ability to interact with the application conversationally using natural language (Feuerriegel *et al.*, 2024). The interface may also include details about the developer, the foundation model used, and the training data. It may also provide instructions and guidelines for use and prohibitions, and to inform users of relevant endorsements. Many commercially available LLM applications have minimal information for users, prompting them to explore on their own and discover uses. LLMs developed specifically for certain use cases, or within certain contexts, may have more precise information available to users, such as Microsoft's Copilot. Common LLM applications include OpenAI's ChatGPT, available as a web application or native app; X's Grok, available exclusively via the X interface; and Google's Gemini, which enables both text and image generation within the same tool.

A GenAI system represents an instantiation of each of these components. Therefore, each component exhibits certain characteristics that can influence alignment. The four components that are likely to have the most potential impact in determining variation in religious value creation are the foundational model, the training data, the tooling layer and the LLM application[7]. First, foundation models instantiate the representations of groups found in the original broad dataset used to develop the model, and as such, may misrepresent certain religious organizations (Tao *et al.*, 2024). Second, for data to be used for contextualized training of a model, it must exist, be available and be digitized. Third, while AI systems are largely inscrutable (Berente *et al.*, 2021), developers of a GenAI system can provide a (sometimes limited) explanation of what approach was used to fine-tune the model and to specify where and how the model searches for responses to queries. These explanations are often probabilistic, just like the initial output, and therefore are subject to error (Feuerriegel *et al.*, 2024). Finally, the LLM application user interface can instantiate transparency, by indicating which foundation model was used, who it was developed by, how it was trained, which data sources were used for training, and when was it most recently updated can all be indicated.

[7] The choice to use public or private cloud infrastructure, and the choice of provider, are important for all types of organizations, religious organizations included. However, the considerations relative to these choices, such as the security of the infrastructure for example, are not unique to religious organizations. Similarly, we do not anticipate that the computing hardware a religious organization might use to run an LLM locally would be significantly different from that of any other type of organization.

1.3 A Configurational Perspective of Fit

Our conceptualization seeks to answer our research question: How does religious authority influence value generation from generative AI for religious organizations? The central proposition of this paper is that *the configuration of fit of the layers of authority of the religious organizations with the generative AI components influences the ability of religious organizations to gain value from GenAI.* The conceptual overview of ISBV literature presented in **Figure 1.1** suggests that ISBV results from fit among IT resources, non-IT resources and other organizational factors. In ISBV literature, performance can be conceptualized in many ways, including market value, shareholder value, organizational productivity and consumer surplus (Melville *et al.*, 2004; Schryen, 2013). **Figure 1.2** below presents an adaptation of this model to the context of religious organizations and focuses on the organizational factor of religious authority and the IT resource of Generative AI.

Not all conceptualizations of performance from the ISBV literature may be relevant to religious organizations, but some do apply. For example, while religious organizations may not be solely interested in financial profit, financial viability and sustainability are important (Miller, 2002). Religious organizations do not have shareholders, but they do have stakeholders, making stakeholder value relevant. Additionally, organizational productivity, or the ability to effectively run religious operations, may be an appropriate conceptualization of value. As noted above, value for adherents – in the form of rewards and compensators – is also important for religious organizations (Miller, 2002). To remain sustainable, a religious organization requires adherents who are committed to the organization's belief system, and so performance of a religious organization can also be measured in terms of the number of adherents and the depth of their commitment (Miller, 2002; Tracey, 2012).

In our theorization (summarized in **Figure 1.2**), we concentrate on the configuration of two groups of factors from the ISBV framework presented in **Figure 1.1**: IT resources and organizational factors. According to our conceptualization, in situations of ideal fit between components of GenAI and dimensions of religious authority, religious organizations will be able to use GenAI to execute religious processes, provide new religious services and activities, and provide these services and activities in new ways, to adherents. Through their participation, adherents receive rewards and compensators (value). This in turn should help these organizations increase the number of their adherents and strengthen adherents' religious commitment, indications of performance for religious organizations.

Our configurational conceptualization of fit (Charles C. Ragin, 1987; Venkatraman, 1989) examines fit between components of a specific technology (GenAI) and an organizational factor (religious authority) and the influence this fit may have on the ability of religious organizations to derive value from generative AI. The configurational view of fit we adopt is profile deviation (Venkatraman, 1989). This view implies that an ideal fit among several factors leads to performance outcomes. It differs from gestalt fit, which refers to the fit of an internally consistent set of factors without specifying performance outcomes. It also differs from mediation and moderation fit, approaches which describe fit between two or three factors only. In our model, profile deviation is appropriate because we posit that ideal fit leads to religious performance outcomes, and that the fit between religious authority and GenAI is not one-dimensional. In each religious organization, certain layers of authority may be more or less important. Similarly, each component of GenAI may be more or less relevant to each dimension of religious authority. A configurational approach allows us to analyze potential successful combinations of both components of GenAI systems and variations in religious authority structures, without imposing a single optimal configuration (c.f. Ragin, 1987).

In the following sections, we explain different configurations of fit between layers of religious authority and components of GenAI. We do not propose a taxonomy of existing religious organizations. Instead, we describe situations of fit among layers of religious authority and components of GenAI. As indicated in section 3.2.2, we examine the layers of religious authority individually for analytical purposes. We begin by explaining the fit between each layer of religious authority with component(s) of GenAI. We then present illustrative examples of the potential for religious value generation in situations of fit, and of how misfit, or absence of fit, may prevent the generation of religious value. Ideal fit is understood as an ideal configuration of all relevant layers of authority (as determined by the belief system) and components of GenAI.

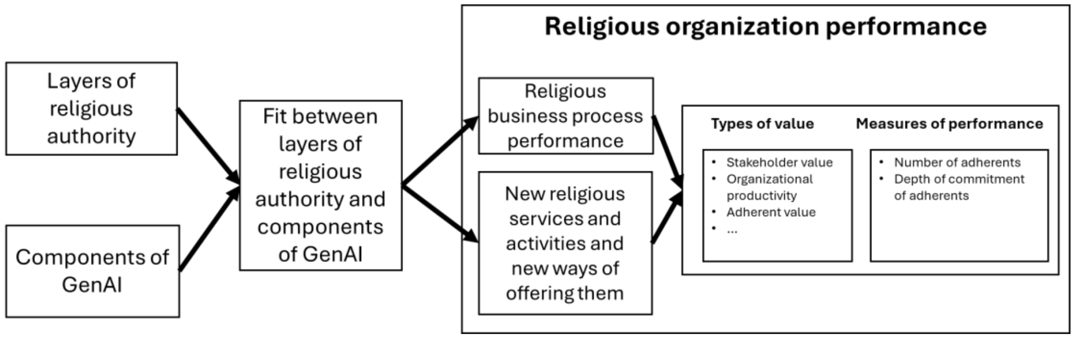

Figure 1-2 GenAI, Religious Value Generation and Religious Organizational Performance

1.3.1 Fit: Authority from Text - Components of GenAI

Fit between text and components of GenAI means that the components of the GenAI system are aligned with, and respect, represent and reflect the important texts of the religious organization. There are three components of GenAI that are relevant to ensuring this fit: training data, tooling layer and LLM application. First, fit is increased when the GenAI system is trained or fine-tuned on a specific text or set of texts (**training data**) the religious organization has determined to be important. This is enabled by the availability and accessibility of relevant data (Vial *et al.*, 2021). Second, fit is more likely if the structure of the model (the **tooling layer**) allows it to reference these specific texts. For example, RAG can be used to ensure the model searches for answers only within a specific and defined body of sacred or religious texts (Huang *et al.*, 2025). Referencing these texts alongside the output is an example of explainability (Berente *et al.*, 2021), as it explains to the user which texts were searched in the generation of the output. Finally, fit is increased when the GenAI system (as shown on the **LLM application** interface) transparently indicates which texts were referred to during the response generation.

1.3.2 Fit: Authority from Ideology - Components of GenAI

Fit between ideology and components of GenAI means that the components of the GenAI system work together to ensure that the output of the GenAI system respects and accurately reflects the ideology, or beliefs, of the religious organization. The three components of GenAI that are relevant to ensuring this fit are the training data, the tooling layer, and the foundation model. An indication of it is when the GenAI system output is able to faithfully represent the ideology of the organization and avoid "hallucinations" (Huang *et al.*, 2025). First, when the **training data** set is contextualized and faithful, and source-reference divergence is minimized, there is less likelihood of hallucination and increased likelihood of the system output adhering to the ideology. Second, fit is more likely when the approach used to train and fine-tune the model (the **tooling layer**) eliminates or minimizes the hallucinations commonly produced by the foundation models used to develop the system. Relevant hallucination mitigation methods include modifying encoder architecture to maximize faithfulness to training data, using reinforcement learning to train the model, or using RAG (Huang *et al.*, 2025). Third, fit is more likely when the **foundation model** does not misrepresent the ideology of the religious organization. Previous studies have shown that many foundation models exhibit latent biases that predominantly favor Western values, and as a result, may misrepresent other groups, including religious organizations (Tao *et al.*, 2024).

1.3.3 Fit: Authority from Community Structure - Components of GenAI

Fit between community structure and components of GenAI means that the components of the GenAI system are configured to represent the way the community exercises religious authority. The two components of the GenAI system most relevant to this fit are the LLM application and the tooling layer. First, an indicator of fit would be a transparent indication of community endorsement within the interface of the **LLM application**. This might be accomplished by including testimonials from users, by indicating the number of community members who have used the tool in recent months, or by displaying current active users. Additionally, fit with authority from community would mean that the GenAI system (the **tooling layer**) would be able to integrate feedback from the community to improve the relevance of the output. This could involve a mechanism within the system that collects user feedback to improve the output.

1.3.4 Fit: Authority from Roles/Leadership - Components of GenAI

Fit between roles or leadership and the components of GenAI means that the components of the GenAI system are configured to demonstrate the support or endorsement of leaders of the religious organization. In the case of fit with roles or leadership, there is one component of the GenAI system that appears relevant: the **LLM application**. Specifically, if authority from roles is an important layer of authority for the religious organization, and if the LLM application can transparently indicate the endorsement from religious leaders, there is greater potential for religious value generation. An indicator of fit would be a clear indication of which religious leaders are using the application, such as by including testimonials from religious leaders who support the use of the application, or examples of uses of the application by religious leaders, within the application interface. **Table 1.1** below summarizes the conditions of best fit between the layers of religious authority and components of generative AI.

Table 1-1 Fit Among Layers of Religious Authority and Components of GenAI

Layer of authority	**Text**	**Ideology**	**Structure**	**Roles/leadership**
What it means	The extent to which religious authority comes from a specific and bounded collection of texts.	The extent to which religious authority comes from the commonly held beliefs and ideas of faith of adherents of a religion.	The extent to which religious authority comes from community structures, patterns of practice or official organizations.	The extent to which religious authority comes from religious leaders.
Conditions of best fit	**Training data**: The GenAI system must have been trained/fine-tuned on a specific text or set of texts as identified by the religious organization as being important. **Tooling layer**: The structure of the model allows it to reference specific texts (for example RAG). **LLM application:** The output of the GenAI system must clearly indicate which texts were referred to during response generation.	**Training data**: The training data set must be contextualized and faithful to the religious organization's belief system, and source-reference divergence must be minimized. **Tooling layer:** Fine tuning must minimize (at least) or eliminate (at best) the hallucinations inherent in foundation models. **Foundation model**: The foundation model must accurately represent the ideology of the religious organization.	**Tooling layer:** The GenAI system must be able to integrate feedback from the community to improve relevance of output. **LLM application**: The interface of GenAI system must clearly indicate the endorsement given by the community (for example, by indicating number of users from within the community, or sharing recommendations from community members).	**LLM application:** The GenAI system must clearly indicate the endorsement of the leaders of the religious organization (for example, by indicating which religious leaders are using it and providing testimonials)

1.4 Ideal fit and religious value generation

Previous literature has determined that fit among organizational factors and IT resources leads to increased organizational performance and value generation potential, via improvements in business process performance and the ability to offer new products and services or to offer products and services in new ways (e.g., Davern *et al.*, 2000; Wade *et al.*, 2004). Based on this theoretical connection, we propose that in situations of fit among layers of religious authority and components of GenAI, religious organizations are able to use religious GenAI systems to generate religious value for adherents and contribute to religious organizational performance. The two primary paths for influencing organizational performance are (1) through enabling religious business process performance, and (2) through offering religious services and activities in new ways and offering new or enhanced religious services and activities. As stated in section 1.2.1 above, religious organizational performance is measured in the number of adherents to a religious organization, and the depth of their commitment to the organization (Miller, 2002; Stark *et al.*, 1980; Tracey, 2012). In the following paragraphs, we provide examples of how this fit may lead to religious value generation, and religious organizational performance.

We will begin by providing an example of the outcome of ideal fit between authority from **text** and components of GenAI. When text is an important layer of authority for a religious organization, and when specific attention is paid to which texts are used to train or fine-tune the LLM, how these texts are retrieved, and how they are referenced in responses provided by the GenAI system, the GenAI system has a high potential of generating religious value. Ideal fit between authority from text and components of GenAI can be illustrated with the example of using GenAI to assist in the provision of religious advice. One benefit for the adherent of receiving religious advice or guidance is their confidence they are properly following the recommendations of the religious organization. An example from Islam is the assurance adherents are following the Muslim "straight path." This could in turn deepen their commitment to the religious organization, a measure of organizational performance. In this example, for religious organizations where authority comes from text, there is more potential of performance of the religious business process of providing religious advice if the GenAI system was explicitly trained on the sacred and important texts of the religious organization to generate religious advice; if explanations are provided as to how the tooling layer references the texts used in generating the output; and if the user interface (LLM application component) of the GenAI system can transparently indicate which texts are used to fine-tune the model.

Next, we provide an illustration of the outcome of fit between authority from **ideology** and components of GenAI. When ideology is an important layer of authority for a religious organization, and when specific attention is paid to aligning the training data, the tooling layer and the foundational model with this ideology, the GenAI system has a high potential of generating religious value. Fit between authority from ideology and components of GenAI can be illustrated with the religious process of learning about a religious organization. One benefit to the adherent is gaining a better understanding of how to achieve enlightenment, a compensator. This could lead to deepening the commitment of the adherent to the religious organization, a measure of organizational performance. In religious organizations where authority comes from ideology, there is more potential of religious value when using GenAI to learn about a religious organization when the GenAI system is able to faithfully represent this ideology by drawing on a contextualized and faithful dataset; if the approach to fine-tuning the model minimizes hallucinations and accurately reflects the beliefs of the religious organization; and if the foundation model that was used to develop the GenAI system does not misrepresent the religious organization, its beliefs, or its adherents.

We now provide an example of the outcome of fit between the layer of religious authority of **community structure** and components of GenAI. When community structure is an important layer of authority for a religious organization, and when the application interface of a GenAI system clearly indicates the support and endorsement of the community, and when such feedback can be integrated into the model, the use of the GenAI system would have high potential of generating religious value. This could be accomplished by displaying information about the active user base via the application interface. For example, the interface could indicate the number of users currently online, or, in the case of a closed GenAI system designed for a limited user base, list which users are currently using the system. Conversely, if authority from community structures is important, but the community rejects the use of a GenAI system for religious purposes (by leaving negative reviews for example), or the GenAI system does not effectively integrate community feedback, there would be a misalignment between religious authority and the tooling layer and LLM application. In such cases, the ability of the GenAI system to generate religious value would be limited. Investments in a religious adaptation of GenAI in this context would not effectively contribute to organizational value or performance

We conclude with an illustration of the consequences of fit between the layer of religious authority from religious **leaders**, and components of GenAI. When authority comes from religious leaders within a religious organization, and when the application interface of a GenAI system clearly indicates the endorsement or approval from these leaders, the GenAI system has a high potential of generating religious value. For example, Magisterium.com is a GenAI system built specifically in line with the Catholic Church. The website for Magisterium.com includes links to media articles and recordings of events, such as the AI Builders Forum hosted by the Pontifical Gregorian University in Vatican City, indicating that the application has the support of the leadership of the Catholic Church. Conversely, if leaders of a religious organization disapprove or forbid the use of a GenAI tool (in general or for specific purposes), and thus no endorsement is visible on the interface, its ability to generate religious value would be limited. Investments in a religious adaptation of GenAI in this context would not effectively contribute to organizational value or performance.

In our conceptualization, the layers of authority have been presented individually, but they are rarely orthogonal in practice: multiple layers may overlap or be intertwined, such as roles and structure, or text and ideology (Campbell, 2007; Gifford, 2005). The perception of a religious leader's authority may be linked with the community structure of the religious organization, as exemplified in the Catholic church, where both the Pope (roles) and the hierarchical structure of the church (community structure) mutually influence each other (McGreavy, 2022)). Similarly, ideology and text may overlap, as a religious organization's ideology is often (but not always) codified in certain texts. Thus, while analyzing each layer of authority individually may not perfectly reflect reality, by breaking down both the layers of religious authority and the components of GenAI, we allow for an exploration of potential configurations of fit that offer a first step in understanding how religious authority and GenAI both contribute to religious value generation from GenAI.

1.5 Discussion

In this paper, we presented a configurational conceptualization of fit between layers of religious authority in religious organizations and components of GenAI. Drawing on literature from digital religion and sociology of religion (e.g., Campbell, 2007; Cheong, 2021; Gifford, 2005) we provided a detailed examination of one organizational factor, namely religious authority, in generating ISBV. We examined the four layers of religious authority individually, to understand the potential impact of each. The literature on management of religious organizations (e.g. Miller, 2002; Tracey, 2012) was mobilized to understand the nature of religious value and the performance of religious organizations. We provided a fine-grained examination of GenAI at the component level which highlighted the ways in which variations in each component come about, and the potential impact of these variations in the context of religious organizations. Finally, we used the ISBV framework as a lens to understand how religious authority and GenAI components must fit together for religious organizations to be able to use GenAI to generate religious value. In the following sections, we present our contributions.

Our work makes five contributions to existing research. Our first contribution is to the understanding of religious value creation and performance of religious organizations when using digital technologies. Research on the management of religious organizations has suggested measures of religious value and performance of religious organizations (Miller, 2002; Tracey, 2012), but to date does not conceptualize the role of IT in generating religious value. Research in communications and religious studies explore how IT is being used for religious purposes (e.g., Campbell, 2007; Cheong, 2021; Hutchings, 2017), but does not directly examine religious value generation from IT. Our application of the ISBV framework in the context of religious organizations allows us to propose a theoretical link between IS investments (in this case GenAI specifically), generation of religious value and performance of religious organizations, contributing a theoretical perspective on how to analyze value generation from IS in this area.

Our second contribution is an extension of the applicability of the ISBV framework, through the proposal of the novel application of this framework in religious organizations. Previous research on ISBV has primarily been conducted in business contexts, where the focus is on financial profit, process performance, or other economic and profitability measures (Melville *et al.*, 2004; Sabherwal *et al.*, 2015; Schryen, 2013). By exploring the configuration of layers of religious authority and GenAI components, we demonstrate the applicability of the ISBV framework to the context of religious organizations. We also open the path for applying the ISBV framework in other, less traditional contexts. This contributes an important building-block to future theorization on ISBV in different contexts, and under different conceptualizations of value (Whetten, 1989).

Our third contribution is to provide a detailed examination of the role of one organizational factor in generating ISBV. While early work on ISBV examined the fit between IT resources and non-IT resources, later work recognizes the need to consider the fit between IT resources and organizational factors (Cao *et al.*, 2011; Schryen, 2013). Religious authority is one organizational factor that is important to religious organizations (Campbell, 2007; Chaves, 1993; Cheong, 2021; Miller, 2002). Furthermore, by breaking down the layers of religious authority, we contribute a nuanced perspective of how religious authority can fit, or not fit, with information systems, specifically with GenAI. As authority can be an important organizational factor in other domains, the detailed exploration of religious authority opens the possibility for a more nuanced examination of the authority construct in other domains. Our detailed examination of the role of layers of religious authority in value generation from GenAI demonstrates the potential value of studying a factor at the dimension level. It also contributes to ongoing efforts to better understand the role of organizational factors in the generation of ISBV (Cao *et al.*, 2011).

Our fourth contribution is to the growing literature that uses configurational theories to understand the role of different combinations of factors in the generation of ISBV. Understanding how organizations can generate value from their IS investments has been a preoccupation of IS literature for decades (Melville *et al.*, 2004; Sabherwal *et al.*, 2015; Schryen, 2013; Wade *et al.*, 2004). Recent works in this area focus on a configurational, rather than a pairwise or moderation view of fit (Cao *et al.*, 2011; Ortiz De Guinea *et al.*, 2022; Wang *et al.*, 2019). By exploring a configurational perspective of fit between religious authority and components of GenAI, we contribute to this ongoing work. By examining the role of each layer of authority separately, we go one step further and propose a more fine-grained conceptualization of configuration among organizational factors and IS investments. The configurational perspective presented in this paper demonstrates the possibility and the value of this fine-grained conceptualization by examining the role of each layer of authority and each component of GenAI.

Our fifth contribution is a demonstration of how the IT resources construct can be disaggregated in an ISBV framework and how this disaggregation can contribute to our understanding of the value-generation potential of IT resources. Previous research has recommended disaggregating the IT resources construct in ISBV research (e.g. Schryen, 2013). Later research examined the differential contribution of different types of IS investments to ISBV by examining different types of IT, and the role and purpose of IT within an organization. These studies have found that not all IT contributes equally to organizational value (Bayer, Haug et Hvam, 2020; Kim, Wimble et Sambamurthy, 2018). Specific to GenAI, Hosanager and Krishnan (2024) proposed examining the components of GenAI individually to assess opportunities for different types of organizations to capture value from GenAI. In our study, we demonstrate the value of applying a framework of the components of GenAI to the study of ISBV, showing how those components can help researchers think through fit. By disaggregating a specific technology into its constituent components, we open a line of inquiry into a more granular examination of GenAI systems when determining their contribution to organizational value generation. Furthermore, while the approach presented in this paper centers around GenAI, this disaggregation approach may also be applicable to other types of IT and digital technologies.

1.5.1 An Agenda for Future Research

The conceptualization proposed in this paper offers many opportunities for future research. One potential direction for future research is empirical validation and refinement of the proposed framework through multiple qualitative case studies of the use of GenAI systems developed specifically for religious organizations. Data collection could involve interviews with developers and users of religious GenAI apps, careful examination of the apps themselves, and detailed analysis of secondary data about these systems. Analysis could focus on understanding the role of the layers of religious authority and their fit with components of GenAI, the nature of the compensators individuals report receiving via religious use of GenAI, and the religious value generation potential of these apps for religious organizations. Similarly, future studies could investigate whether GenAI is more likely to generate religious value in the hands of adherents or religious leaders, or if different types of religious value can be generated depending on who is using it and how. This investigation may elucidate whether the use of GenAI changes religious processes or the value they can generate for adherents and for organizations.

In this paper, we explore the use of GenAI to create religious value, but future research could also look at GenAI and its potential to reduce or destroy religious value. One of the risks to religious value from GenAI is hallucination. Religious authority plays a role in controlling the "truth" of a religious organization. Hallucinations are potentially very problematic in religious contexts, as they threaten the understanding of religious "truth". Future research could involve a detailed examination of the types of hallucinations that could be problematic, the potential negative effects of hallucinations in use of GenAI for religious purposes, or the effectiveness of hallucination mitigation approaches and their alignment with religious authority. Similarly, future research could explore the challenges of maintaining a single organizational "truth" while adherents have access to many sources. Previous research has suggested the need to monitor the use of the Internet for Islamic purposes to keep users on the "straight path" (Lawrence, 2002). It may therefore be important to understand the role monitoring plays in the context of religious GenAI, to ensure it continues to create, not destroy, religious value.

A third area of potential study is the impact of GenAI on religious authority. While we present components of GenAI and layers of religious authority as two exogenous factors in the generation of religious value from GenAI, GenAI may impact or change religious authority in unexpected ways. Extant research has examined the effects of the internet and other new media on religious authority, including the emergence of new authority roles like webmasters and moderators of online forums (e.g. Campbell, 2007), the delocalization of religious authority from traditional roles, and the re-embedding of religious authority as religious leaders gain new skills (Cheong *et al.*, 2011). Developing and deploying religious GenAI applications requires both technical and religious skills. Future research may uncover challenges to or reinforcement of religious authority through the integration of GenAI in religious organizations, depending perhaps on the original skills and expertise of the developers.

A fourth potential area of future research is applying the ISBV framework more broadly. Our conceptualization focuses on the components of GenAI and the layers of religious value as instantiations of two constructs within the ISBV framework. Future research could apply other instantiations of these constructs, or additional constructs of ISBV framework to the context of religious value generation using GenAI. This would allow for a more holistic examination of all factors that influence how religious organizations might generate religious value from GenAI. For example, several sociocultural factors could be important for value generation from GenAI systems. One such factor is digital literacy, or the ability to understand and use digital technologies such as GenAI. This may impact adherents' ability to effectively use GenAI systems. A second factor is the political and regulatory environment, which may enable or constrain development and deployment of religious GenAI. A third factor is the theological perspectives a religious organization may have adopted on AI. For example, the Ethics and Religious Liberty Commission released an Evangelical Statement of Principles in 2019 on Artificial Intelligence (ERLC Staff, 2019). An emerging stream of literature addresses the relationships between Sikhism and artificial intelligence (e.g., Singh, 2023, 2024). Similarly, technological factors may influence religious value generation from GenAI. These include technological advances which may increase the precision of text retrieval and analysis and enable seamless integration of GenAI into human communication in a variety of contexts. These advances may increase or decrease inscrutability of AI algorithms.

1.5.2 Limitations

This study has several limitations. One limitation is the artificial disaggregation of layers of religious authority. In this study, the layers of authority were presented individually for the purpose of analyzing potential alignment with GenAI components. This allows for a nuanced examination of the role each layer may play, highlighting the differential role each layer of authority may play in different religious organizations. In reality, layers of religious authority overlap and are intertwined (Gifford, 2005). For example, ideology may be codified in texts, religious leaders may rely on texts and in some cases contribute to the creation of new texts, and community structure and religious leadership may be suggested or determined by ideology. This means that in practice, the layers of religious authority cannot and should not be analyzed solely in isolation. Researchers seeking to conduct empirical research to test the conceptualization in this study must carefully consider its operationalization to ensure that religious authority of a religious organization is appropriately assessed or measured.

A second limitation of this study is its focus on religious organizations specifically. Some scholars of sociology and religious studies have said that religious organizations are considered as a distinctly Western concept (Dubuisson, 2003), and that the concept of “religious organization” may not accurately capture all religious groups, beliefs and practices (Platvoet et Molendijk, 1999). By focusing on religious organizations rather than religious experience or belief more generally, the generalizability of this study to all religious contexts may be limited. Despite this potential limitation, the concept of religious authority is likely relevant in contexts outside of strictly organized religion, and the conceptualization proposed in this paper may therefore still be relevant.

A third potential limitation of this study is its reliance on five specific components of GenAI and four specific layers of religious authority. While these layers of authority are grounded in literature (Campbell, 2007), there may be other layers of authority beyond the four presented in this study. The five components of GenAI presented in this study apply to text-based GenAI (Hosanagar *et al.*, 2024), but there may be religious uses of other types of GenAI that include different or additional components. Similarly, as GenAI systems are constantly evolving, there may be additional components to be considered beyond the five presented here. Researchers interested in applying the configurational perspective proposed in this paper should be open to integrating additional layers of authority or components of GenAI, if they are applicable in the context of their study.

1.6 Conclusion

We have presented a configurational theory of the role of the fit between GenAI components and layers of religious authority for religious value generation from GenAI. Our conceptualization contributes to extant research in five ways: we contribute to the understanding of religious value generation from IS in religious organizations; we extend the ISBV framework by demonstrating an application of its use in religious organizations; we present a detailed examination of one specific organizational factor relevant to religious organizations; we contribute to ongoing work exploring the configurational nature of ISBV; and we demonstrate the benefit of disaggregating the IT resources construct by examining the components of GenAI. We concluded by providing several directions for future research, including empirically testing the conceptualization proposed in this paper, and applying similar approaches in other contexts.

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Chapter 2
Managing AI Within a Complex Supply Chain Ecosystem: The AISys Project at CityPort

Abstract

Organizations in many industries are trying to improve their operational logistics by implementing artificial intelligence (AI). AI is emerging as a powerful tool to help organizations develop agile supply chains that can rapidly respond to internal and external pressures. Successfully managing a rapid AI project within a complex supply chain ecosystem requires extensive domain and AI expertise and project management skills, and an ability to respond to challenges throughout the project. This study adopts a team-level coping perspective to understand how an organization can manage the stressors of a rapid, complex AI project. This paper reports on a single case study of an AI supply chain ecosystem project conducted during the early days of the COVID-19 pandemic at a major international maritime port with the goal of identifying and expediting critical personal protective equipment. This study makes three contributions. It brings to light how socialization, or specific actions intended to modify the behavior of other organizations, can be beneficial for multi-organizational AI projects. It suggests that strategic overstaffing of data science experts – in particular retaining experts familiar with the project and the environment within the "orbit" of a project, available to assist if needed – can help accelerate an AI project in a complex environment. It also suggests that organizations wanting to carry out a portfolio of AI projects should engage in strategic data assessment blueprinting, when the advantage conferred by the ability to quickly respond to changing market conditions outweighs the potential cost of a comprehensive data assessment.

2.1 Introduction

"When I speak with clients from outside of our city and they hear that we did an ecosystem AI project with data sharing in supply chain, everyone says 'Wow! How did you do that?'" (Product Manager, BizAI – developer of AISys)

"[AISys] uses AI to quickly identify and prioritize the critical cargo that [people] need to avoid supply delays and stock shortages during [the early months of the COVID-19 pandemic]" (Press Release)

CityPort and BizAI unveil AISys after only 12 weeks: "The project was record-breaking fast" (Director of Innovation, CityPort)

Organizations in many industries are trying to improve their operational logistics by implementing artificial intelligence, and many strive to reproduce the success of the AISys project (described above) which was developed for a complex logistics ecosystem on a tight timeline. Artificial intelligence (AI) is defined as machines performing cognitive functions usually associated with human minds, including solving problems, interacting, and learning (Raisch & Krakowski, 2021). It is emerging as a powerful tool to help organizations develop agile supply chains that can rapidly respond to internal and external pressures (Baryannis *et al.*, 2019; Belhadi *et al.*, 2021; Younis, Balan et Malek, 2022). Successfully managing a rapid AI project within a complex supply chain ecosystem requires extensive domain expertise, AI expertise, and project management skills, and an ability to respond to challenges throughout the project (Lou et Wu, 2021).

It is predicted that by 2027 nearly 80% of supply chain companies will have adopted AI techniques (Statista, 2021). Integrating AI has been shown to positively impact supply chain operational performance in many ways (Hangl, Behrens et Krause, 2022; Helo et Hao, 2022). AI systems are expected to increase supply chain visibility and agility (Belhadi *et al.*, 2022; Pournader *et al.*, 2021). The increase in information processing capabilities through the use of AI-based systems improves decision support, risk management, optimization of strategic and tactical processes, and can improve operations within supply chains (Mariappan *et al.*, 2022; Modgil *et al.*, 2021; Pournader *et al.*, 2021). AI can help align supply and demand and increase the accuracy of predictions, thereby reducing uncertainty and increasing the resilience of supply chain actors in the event of disruptions (Belhadi *et al.*, 2021; Modgil *et al.*, 2021; Younis *et al.*, 2022).

The development and implementation of AI to support an organization's logistics is often organized as an AI project, defined as "*an undertaking that aims to deliver a working software product or service that embeds AI functionality, to be used by humans or machines toward the accomplishment of an objective*" (Vial *et al.*, 2023 : 670). There are several challenges in managing the development and implementation of AI-based systems, particularly in complex contexts like supply chains. For these systems to be effective, organizations must collaborate and promote system interoperability, both of which are difficult to achieve (Brinkhoff, Ozer et Sargut, 2015; Jensen, Vatrapu et Bjorn-Andersen, 2018; Nand *et al.*, 2023; Wu, Chuang et Hsu, 2014). Data sharing among organizations is required, and has an important impact on performance (Modgil *et al.*, 2021; Wu *et al.*, 2014), but does not always happen in practice (Shekarian et Mellat Parast, 2021; Wixom *et al.*, 2023). Even when inter-organizational collaboration, system interoperability and data sharing are optimal, it remains a challenge to manage cultural change within organizations so that the output of these systems can have a concrete impact on physical operations (Hangl *et al.*, 2022).

Extant research on AI project management notes that AI projects benefit from interdisciplinary teams of experts, including those with skills in data science and software engineering (Lebovitz, Levina et Lifshitz-Assaf, 2021; Reis *et al.*, 2020; Vial *et al.*, 2023). Access to quality data is essential for AI projects (Vial *et al.*, 2021). AI systems are both highly technical and inherently opaque in nature which can affect how users respond to them (Asatiani *et al.*, 2021; Lebovitz, Lifshitz-Assaf et Levina, 2022; Pachidi *et al.*, 2021; Zhang *et al.*, 2021). Emergent approaches to manage this opacity during system implementation include envelopment and codification of different types of expert knowledge (Asatiani *et al.*, 2021; Lebovitz *et al.*, 2022). However, most extant research describes long-term projects conducted over several months or even years and therefore does not address the development of AI projects in rapid, urgent contexts.

Thus, this study seeks to answer the question *How can an organization successfully manage a rapid AI project within a complex supply chain ecosystem?* To address this research question, we conducted a single case study of an AI supply chain ecosystem project conducted during the early days of the COVID-19 pandemic at a major international maritime port with the goal of identifying and expediting items critical to responding to COVID-19 at that time. The case study data was analyzed using analytic induction(Patton, 2002). Specifically, the process of team-level coping (Lazarus *et al.*, 1984; Leprince, D'Arripe-Longueville et Doron, 2018; Lyons *et al.*, 1998) was used as a theoretical lens for the initial data analysis of how the project team coped with stressors including the urgency stemming from the COVID-19 pandemic, the complexity of the supply chain ecosystem and the technical difficulty of developing an AI system.

This paper provides a up-close, rich examination (Rai, 2017) of a case of rapid development and implementation of a supply chain ecosystem AI project, resulting in three main insights. The first is the role played by socialization and orchestration activities (Dolmans *et al.*, 2014; Roehrich *et al.*, 2023) by the client in addressing the complexity of the supply chain, data quality and accessibility and low technical maturity. The second is how engaging in strategic data science overstaffing can allow an organization to accelerate an AI project. The third is a recommendation for some organizations in certain circumstances to engage in data blueprinting, normally the first phase of an AI project, in a regular, strategic fashion.

In the following sections we provide an overview of coping theory, which was used as a theoretical framework to analyze the case. We will then describe the methodology and present the case and findings. The discussion examines the key insights from this case and how they can apply to the management of rapid AI projects in complex settings and offers three propositions that emerge from our findings.

2.2 Literature Review

Guided by our research question, as well as our knowledge of the context of the case, we searched the literature on project management in several related contexts to better understand the recommended practices relevant to the case environment: managing IS projects; managing AI projects; managing complex projects; managing supply chain projects; managing urgent projects; fast response/crisis response management; and management in disaster response organizations. The recommended practices identified from our review are presented in four categories: strategic practices; project practices; team/people practices; and process practices(Ellwood, Grimshaw et Pandza, 2017; Kessler et Chakrabarti, 1996). The recommended practices that emerged from the review of these various literatures are presented in **Appendix E** and synthesized in **Table E-1**.

Strategic practices stem from strategic orientations and decisions made before the project begins or in the very early stages, or strategic orientations and decisions that may affect the entire organization. Common across most project management contexts reviewed is the importance of ensuring top management support (Ahern, Leavy et Byrne, 2014; Brinkhoff *et al.*, 2015; Brown et Eisenhardt, 1995; Esteves et Pastor-Collado, 2002) and focusing on project stakeholders beyond the client (Barki, 2008; Bell, Nov et Tandon, 2023; Locatelli, Mancini et Romano, 2014).

Urgent projects prioritize speed above all metrics, making time a goal (Wearne et White-Hunt, 2014). AI projects require specific resources (Lee *et al.*, 2023; Lou *et al.*, 2021), including data, which must be accessible (Vial *et al.*, 2023). They often involve organizational change and may involve unintended consequences, therefore change should be managed (Asatiani *et al.*, 2021). Supply chain projects should take a systems engineering approach to project governance, as effective coordination and information exchange is crucial for these projects (Brinkhoff *et al.*, 2015; Locatelli *et al.*, 2014; Oliveira et Lumineau, 2017; Roehrich *et al.*, 2023; Ryoo et Kim, 2015; Wu *et al.*, 2014). It is unclear however which specific practices, and what type of top management support, can be most beneficial for urgent supply chain projects involving AI.

Project practices are those specific to managing and overseeing the project (such as scheduling and control). In most project management contexts, it is recommended to be open to change, welcome change and build flexibility into the project management process (Ahern *et al.*, 2014; Conboy, 2009; Saynisch, 2010). AI projects should begin by determining data ground truth and adopt conservative approaches (Eckroth, 2020; Lebovitz *et al.*, 2021; Vial *et al.*, 2023). For supply chain projects it is important to focus on process standardization so they can be integrated (Brinch, Gunasekaran et Wamba, 2021). It is therefore unclear whether AI projects in a supply chain ecosystem benefit from flexibility or standardization, nor is it clear what approach is best for ensuring adequate access to necessary data.

Team/People practices refer to how the project team is staffed, including project leadership. Project championship is important and can be shared or distributed (Campion *et al.*, 2022; Negoita *et al.*, 2022; Vial *et al.*, 2023). In most contexts it is recommended to adopt cross functional, interdisciplinary teams of experts (Dremel *et al.*, 2017; Gronsund et Aanestad, 2020; Vial *et al.*, 2023). AI projects require software development and data science technical skills (Vial *et al.*, 2023) which can be in high demand (Davenport et Patil, 2022). Conversely, disaster response literature shows that the team that responds to a disaster is often ad-hoc and lacks specific expertise (Majchrzak, Jarvenpaa et Hollingshead, 2007). It is therefore not clear whether urgent AI projects should be developed by a team formed of individuals with specific expertise or those who are available and motivated to help, nor how to ensure qualified team members are available to help for an urgent project.

Process practices refer primarily to the choice of approach such as an iterative or sequential approach. In most contexts it is recommended to use iterative agile approaches, or hybrid agile/plan-driven approaches (Conboy, 2009; Cram, 2019; Dingsøyr *et al.*, 2012; Gronsund *et al.*, 2020; Vial *et al.*, 2023). AI projects benefit from a hybrid approach, combining phases of development with agile iterations between (Butler, Vijayasarathy et Roberts, 2020; Scheepers, Lacity et Willcocks, 2018; Vial *et al.*, 2023). Most AI projects begin with a blueprint phase during which data is assessed. Detail is lacking, however, on how to best combine agile and plan-driven approaches, particularly for urgent AI projects in a complex supply chain ecosystem.

As the literature review demonstrates, the literature about the management of various types of projects provides a list of practices, many of which are focused on what the project team or leadership can control or manage at the outset of a project, or how to build resilience to unexpected project events. Many types of projects, including complex or urgent projects, can be stressful for project teams. However, less is known about how project teams respond to stress during a project, what resources they have at their disposal and what strategies they employ. Team-level coping theory (Lazarus *et al.*, 1984; Lyons *et al.*, 1998) provides a framework with which to understand the process by which a project team responds to stressors during a project.

2.3 Theoretical Background

This study examines how an organization can successfully manage a rapid AI project within a complex supply chain ecosystem. Projects of this size and nature are conducted by a team, defined in this study as a professional entity, composed of members from one or multiple organizations, with a high level of task interdependency, and shared values and common goals (Salas, Cooke et Rosen, 2008). To understand how the project team managed to deliver a successful project despite the various pressures, we draw on a team-level adaptation of the transactional model of stress and coping (hereafter referred to as "coping theory") (Beaudry et Pinsonneault, 2005; Bhattacherjee *et al.*, 2018; Lazarus *et al.*, 1984). We use coping theory as a theoretical lens with which to conduct our data analysis (Niederman et March, 2019).

2.3.1 Relevance of Coping Theory

There were several reasons why coping theory was an appropriate theoretical lens with which to preliminarily analyze the case data. First, disruptive events often occur in projects, causing stress to project team members (Thielsch *et al.*, 2021). A preliminary analysis of the data indicated that the project team faced several stressors, including but not limited to time pressure, which can be an important project stressor (Pearsall, Ellis et Stein, 2009). Second, coping theory posits that the appraisal of both a stressor and the response possibilities are important. Project risks can be viewed as opportunities or threats. In the AISys project, the appraisal of the challenges the project team encountered seemed to influence the project team responses. The resources they had at their disposal, and their appraisal of these resources, were also salient in the interview responses. Finally, coping theory notes that individual appraisal of stressors and coping responses can change over time (Lazarus, 1993). Different stressors emerged over the course of the AISys project. To ensure that coping theory was the appropriate lens, we initially tested three other theoretical lenses: the empathy-altruism hypothesis (because of the desire to "save lives" expressed by project team members); as well as two theories of stress: the job-demands-resources theory and the challenge-hindrance model. See **Appendix F** for an explanation of why these three theories were not retained.

2.3.2 Team-level Coping Theory

Coping theory was originally developed as an individual-level theory that explains the cognitive and emotional processes individuals go through when they respond to stressful events or situations. The coping process begins with appraisal of the stressor, then individuals appraise response possibilities and finally respond to the stressor by employing coping strategies. Successful coping allows individuals to reduce the impact of stress and therefore allow them to focus on their performance (Beaudry *et al.*, 2005; Lazarus *et al.*, 1984). Adaptation to stress is an iterative process: individuals alternate between appraisal and adaptation strategies (Beaudry *et al.*, 2005; Lazarus, 1993).

Coping theory has been adapted to the group, or team level in research (e.g. Liu *et al.*, 2018). For the most part, the constructs in coping theory are isomorphic at the team level. Team stress occurs at the team level (Benlian, 2022; Leprince *et al.*, 2018; McCarthy *et al.*, 2023), and sources of stress can be exogenous or endogenous to the group (Liu *et al.*, 2018; Nurmi, 2011). However, one additional mechanism at play in team-level coping is the extent to which the coping process is communal. Communal coping refers to appraisal of the effect of stress on the group rather than the individual, and the employment of coping strategies that benefit the group, even if the outcome does not benefit the individual (Lyons *et al.*, 1998). Team-level research using coping theory has been conducted in experimental settings using student subjects (e.g. Ellis et Pearsall, 2011; Pearsall *et al.*, 2009), and on intact work teams in industries including banking, food service, telecommunications, new product development and sports teams (e.g. Chong *et al.*, 2010; Liu *et al.*, 2018; Nurmi, 2011; Wolf *et al.*, 2015).

Primary appraisal is the appraisal of the stressor as a threat or opportunity. Primary appraisal can be a result of social interactions among team members (Liu *et al.*, 2018). Stress can be appraised at the individual or team level (McCarthy *et al.*, 2023; Nurmi, 2011), and there may be cross-level influences in primary appraisal (Espedido, Searle et Griffin, 2020). In team or group environments, primary appraisal of a stressor can also include an assessment of the extent to which the stressor represents a threat or an opportunity for the group and not just the individual (Lyons *et al.*, 1998).

Secondary appraisal is appraisal of the extent of control the group has over the stressor. It involves the appraisal of the group's ability to respond and includes the appraisal of their resources – both the individual resources of group members and the team-level, or communal resources (Lyons *et al.*, 1998). Communal resources include team skills and education (e.g. Dasí *et al.*, 2021; Hansen, Vaagen et Van Oorschot, 2020; Wolf *et al.*, 2015); collective efficacy (i.e. expertise and information within the team) (Thielsch *et al.*, 2021; Vera, Rodríguez-Sánchez et Salanova, 2017); intra-organizational relationships, good teamwork, organizational practices (i.e. a good team dynamic) (Thielsch *et al.*, 2021; Vera *et al.*, 2017; Wolf *et al.*, 2015); transformational leadership (Vera *et al.*, 2017); inter-organizational relationships and access to a stakeholder network (Thielsch *et al.*, 2021); and other organizational and environmental resources, including available technology (Dasí *et al.*, 2021; Nurmi, 2011).

Following appraisal, teams will employ team-level **coping response strategies** to address team stress and reduce strain (Espedido *et al.*, 2020; Nurmi, 2011; Pearsall *et al.*, 2009). Coping strategies have been categorized two ways: as problem-focused – i.e., focused on actively addressing a controllable source of stress – or emotion-focused – i.e., emotional regulation when the stressor cannot be controlled; and as adaptive – i.e., focusing on regulation of the situation or of emotions – or maladaptive – i.e., avoiding addressing the stressor or its impacts altogether (Biggs, Brough et Drummond, 2017). Team-level coping strategies can focus on adapting the team's emotional response, for example through interpersonal emotional regulation, de-dramatization, or adapting to the situation by refocusing or expending extra effort (Leprince *et al.*, 2018). One goal of team-level coping is to reduce group strain and restore the well-being of the group, allowing the group to perform (Benlian, 2022; Lyons *et al.*, 1998).

2.3.3 Preliminary Theoretical Framework

In this study, coping theory was used as a theoretical lens to guide the initial round of coding of the data. A preliminary theoretical framework based on team-level coping was used to guide the initial round of coding of the data (Miles, Huberman et Saldana, 2013; Patton, 2002) (see **Figure 2-1**). This preliminary framework represented the process of primary and secondary appraisal of stressors and response possibilities, strategies, and how the coping response impacted the project outcome. Based on our understanding of the project and its context, the preliminary framework modeled the stressors as COVID-19 induced urgency and AI-related complexity. Coping resources were what the team possessed, including expertise, experience, knowledge and technology (e.g. Dasí *et al.*, 2021) and coping response strategies were the actions taken by the project team.

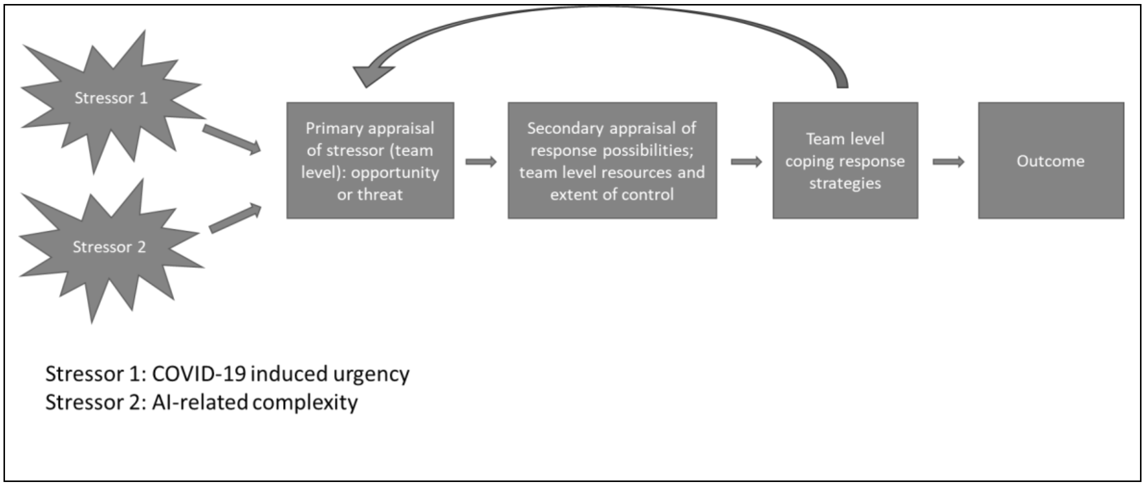

Figure 2-1 Theoretical model of project team level stress and coping (adapted from Beaudry and Pinsonneault 2005 and Lazarus and Folkman 1984).

2.4 Research Method

2.4.1 Research Design

This study reports on a single case study conducted from a positivist perspective (Dubé et Paré, 2003). This methodology can provide insight into an understudied phenomenon when the researchers have privileged access (Eisenhardt et Graebner, 2007; Ozcan, Han et Graebner, 2017). The case in this study is revalatory (Yin, 2014), an approach used when the object of study has been previously inaccessible to inquiry. This case fits this definition because it is a rare example of a successful urgent complex AI development project, for which the research team had privileged access to both the developer and the client.

2.4.2 Case Description

This case examines the development of the system "AISys"[8]. AISys was an AI-based system developed by an AI consulting firm, BizAI, for CityPort, a multimodal port in North America with goods arriving and departing by water, rail, and road. It was designed and delivered in the early weeks of the COVID-19 pandemic to identify and fast-track cargo containers carrying items (primarily personal protective equipment or *PPE*) deemed critical by the local government. In the

[8] All names used in this essay are pseudonyms.

early weeks of the pandemic, PPE was shipped by air, but as the pandemic continued, these supplies were eventually also shipped by sea and arrived at CityPort. At the time, there was concern about the “dwell time” of these containers, or the amount of time a container spends in a port’s operational area. Dwell time is considered a critical metric in port operations. The project goal was to reduce the dwell time of containers carrying critical cargo from an average of three days to less than 12 hours. General port operations are summarized in **Figure 2-2**.

A maritime container port consists of three main areas. Ships are first unloaded in the **operational area**. Containers are stacked and stored once they have been unloaded by terminal operators in the **container yard**. At CityPort, containers can be stacked up to four high, three long and at least 15 deep. The **landside operations area** includes the gate, administrative offices including customs, and is where empty containers are stored, and containers are repaired (Hervás-Peralta *et al.*, 2019).

Ports in general, and port terminals more specifically, have limited capacity and therefore want to optimize their efficiency (Carlan *et al.*, 2017). One way to do this is by reducing **dwell time**. Dwell time can be defined as the total amount of time spent by a container in a port terminal in one or more stacks (Ottjes *et al.*, 2007).

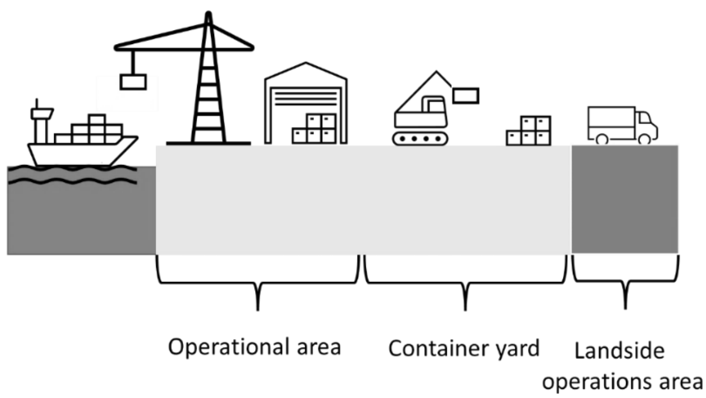

Figure 2-2 The three main areas in maritime port operations (adapted from (Hervás-Peralta et al., 2019))

The three core AISys project organizations were CityPort, BizAI and LogistiCluster, a local transportation and logistics alliance. The broader AISys project organizations also included other companies active at CityPort: rail companies, some trucking companies, some terminal operators, and some shipping lines. The supply chain ecosystem included all transportation companies, logistics companies and importers/exporters. The project required the active collaboration of approximately 15 organizational partners across the ecosystem, including CityPort, BizAI, and LogistiCluster as well as shipping lines, terminal operators, and rail transporters. An overview of the role of project stakeholders is presented in **Table 2-1** below. **Figure 2-3** provides a visual illustration of the local supply chain ecosystem.

Table 2-1 Summary of stakeholders involved in the AISys Project

Stakeholder (pseudonym)	**Description of activities and role on project**
Client (CityPort)	CityPort is a major North American port. In 2020, CityPort handled 1.6 million containers were handled. In 2020 approximately 50% of cargo was outgoing and 50% was incoming. CityPort owns 100km of railway and is responsible for unloading and loading trains that arrive at and leave from the port. The IT, logistics, and strategy departments at CityPort were directly involved in the AISys project, by providing insight into operations and training end-users during implementation, by assisting with the integration of AISys into CityPort's systems and operations, and by providing project management support. At CityPort, the project manager devoted at least 60% of his time to the project. The Director of Innovation, the Director of IT, and the Director of Logistics were involved almost daily. Additional staff from the IT department participated in the integration of AISys into CityPort systems.
Supplier (BizAI)	BizAI was founded in 2017. In early 2020, it employed 60-70 employees, including software developers, data scientists, project and product managers, and scientific advisors. Most projects at BizAI use a combination of AI techniques and traditional optimization techniques from operations research. BizAI's focus is developing AI systems for supply chain clients. BizAI was responsible for the technical development of AISys. Six staff members from BizAI were assigned to the project: two senior developers, one senior AI consultant who acted as project liaison with CityPort, two data scientists, and a technical lead. Acting in a supervisory and advisory capacity were the Product Manager, who allocated about 40% of their time to the project and two scientific advisors who were available 1 day per week. Several Directors and VPs from BizAI would also attend steering committee meetings and provide other support.
Local transportation alliance (LogistiCluster)	LogistiCluster was an alliance founded in 2013 whose goal was to act as a central hub for local transportation companies. LogistiCluster members included transportation companies of different sizes, such as trucking companies, railroads, shipping companies and other logistics companies. LogistiCluster hosts events, produces publications, advocates for the sector and pilots several initiatives. One of LogistiCluster's four focus areas was improving the fluidity of the local transportation sector. LogistiCluster's role in the AISys project was to represent the interests of the local cargo transport industry and to promote the project to local companies. The General Manager of LogistiCluster participated in AISys project steering committee meetings and acted as a liaison between the project team and the transportation companies that were members of LogistiCluster.

Terminal operators	Both container terminal operators at CityPort were involved in AISys. The terminal operators were responsible for unloading arriving cargo, storing cargo on the port lands, and loading containers on to trucks and ships that leave CityPort. The terminal operators used the output of AISys to plan their operations.
Transportation companies	Six international shipping companies, and several rail and trucking companies were partners of the AISys project. These companies all handled the shipment of goods. Shipping companies provided data on incoming cargo for the AIsys project, and ground transportation companies used the output of the system in planning their operations.
Funding agency (AIFund)	AIFund was a federal funding agency that provided matching funding for projects that use AI within the supply chain. In early April 2020, AIFund announced funding available for projects using AI to address COVID-19 supply-chain related issues. These projects were funded 100%. In total eight projects received funding

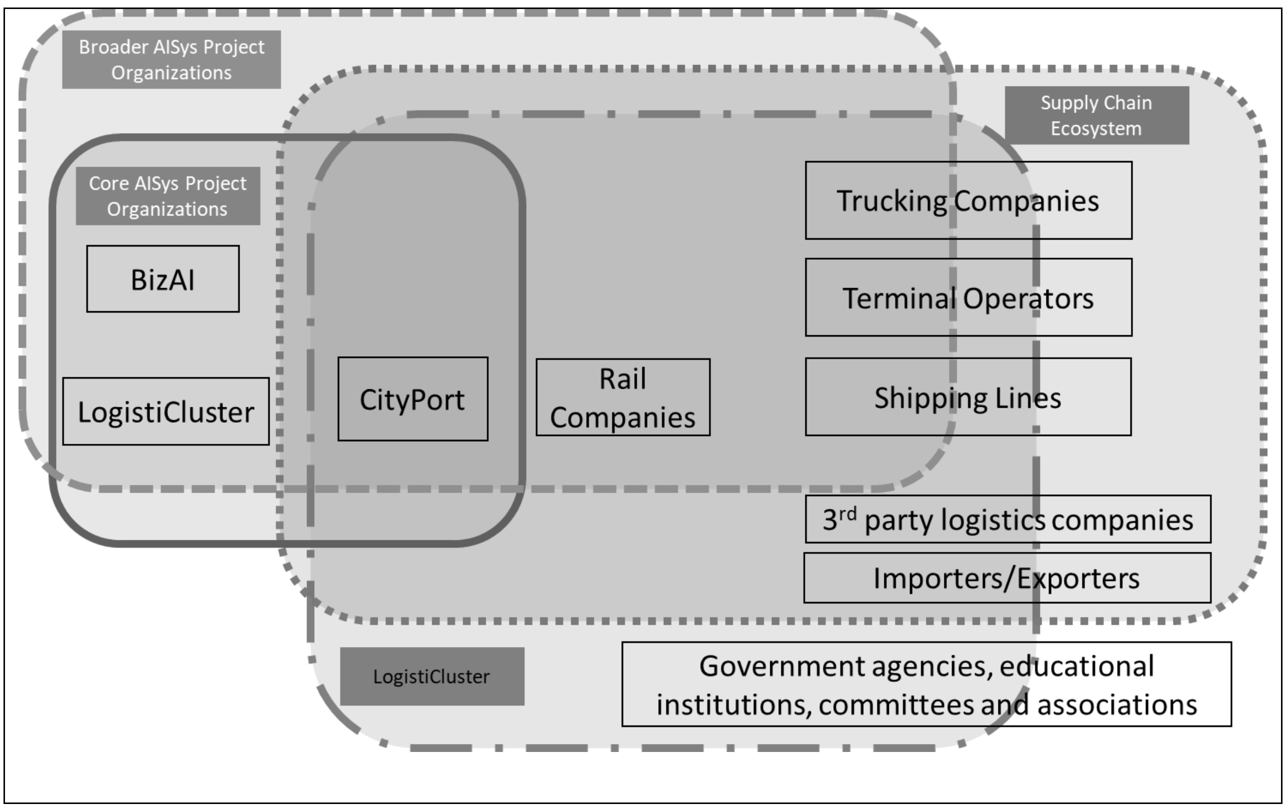

Figure 2-3 AISys Ecosystem

2.4.3 The Tool (AISys)

AISys was developed at a time when the only tools available to combat COVID-19 were various types of PPE. The goal of the system was to fast-track such items through the port to their final destination, by identifying them while still in transit. Data sources used for AISys included cargo manifests and customs declarations provided by international shipping companies to federal customs in compliance with legislation, and port logistics reporting. The manifests were of a standard format and items are identified using Harmonized System (HS) codes, an international classification system. However, sometimes these documents were not completed correctly or had hand-written information added. In addition, the HS system was updated every five to 10 years, and therefore not all item descriptions and corresponding HS code were sufficiently granular to be useful in identifying critical PPE. For example, "alcohol-based hand sanitizer" shared the same HS code as "disinfectant" but uses can differ significantly. The concentration of an alcohol-based solution, and the size of the container, were not necessarily indicated using distinct codes. The same was true for "surgical masks" and "N95 masks" – while both were important in the fight against COVID-19, their uses and destinations were different. Port logistics reporting included information on how and where containers should be stacked in the container yard, and the destination of each container. Information identifying critical cargo needed to be combined with logistics information to identify containers for fast-tracking.

The system therefore used natural language processing (NLP) techniques to complete and correct information provided in cargo manifests, combined with a search algorithm to identify critical cargo. In addition, when looking for "gloves" for example, AISys was trained to differentiate between surgical or latex gloves and baseball or costume gloves. This information was combined with information identifying the destination of critical containers and their mode of transportation. Results were validated by a port employee (a human in the loop). These validated results were then shared with ground operations organizations and integrated into their systems and processes to be used to plan the unloading of ships once they arrived and the ground transportation of containers leaving the port.

2.4.4 The AISys Project

2.4.4.1 Origin Story

In the fall of 2019, CityPort wanted to optimize port ground operations using AI to provide upstream visibility on incoming container ships. CityPort approached BizAI to build a system, which we refer to as PortOpsAI. Between October 2019 and February 2020 BizAI conducted a "blueprint" data assessment. During the data assessment, BizAI had access to CityPort's data and infrastructure, and data provided to CityPort by other organizations in the local ecosystem. In

April 2020, BizAI was ready to develop a proof of concept for PortOpsAI but PortOpsAI was put on hold because in the spring of 2020, AIFund, a federal government agency, announced funding for AI supply chain projects to tackle the COVID-19 pandemic. CityPort, BizAI and LogisitCluster jointly applied for funding for the project that would become AISys.

The AISys project was conducted in two phases. Phase 1 was an initial proof of concept that was developed and put into production between mid-April and mid-July 2020[9]. At the project outset, AISys was supposed to be a static dashboard that identified critical cargo carrying containers. The output would be a CSV file that could be easily exported or emailed to operators (rail and ground transportation terminals). At the end of phase 1, AISys was an interactive dashboard that integrated data about container contents and final destinations that highlighted containers to be fast-tracked. The project was put into production in July 2020 and then launched large scale in September 2020. Phase 2 (not a focus of this study) involved refinement and further development of the project (October 2020-June 2021).

Phase 1 of the project was completed on time, on budget and met requirements. The system output could identify critical containers most of the time, and dwell time of these containers was reduced overall in the months following its implementation. The outputs of AISys were discussed on daily operations calls between CityPort, port terminal operators and ground transportation officials. However, the initial version of AISys delivered to CityPort had several code defects reported by the team at CityPort. In addition, factors out of CityPort's control related to physical availability of both workers and machinery hindered CityPort's ability to consistently expedite critical containers. Nonetheless, the project was considered a strategic success for the three core partners. For CityPort, it helped improve understanding of port operations for their executives and improved their reputation. The project gave BizAI visibility and notoriety, at a time when few AI projects were successful. It also prompted an increased awareness, understanding and interest in AI from many businesses in the entire local ecosystem. The project timeline is summarized in **Figure 2-4**.

[9] The project team referred often to the system deployed at the end of Phase 1 of the AISys project as a "proof of concept" and stated that they put the proof of concept into production. Usually, a proof of concept is tested using historical data and a minimum viable product is tested using live data. However, according to the respondents from BizAI, the system put into production at the end of Phase 1 was closer to a proof of concept than a minimum viable product.

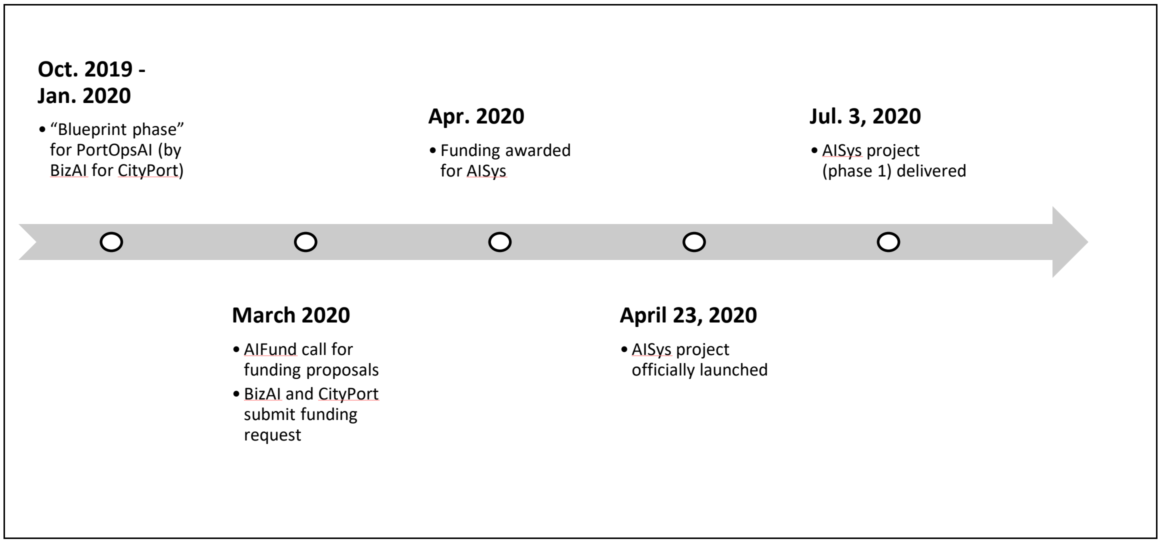

Figure 2-4 AISys Project Timeline

2.4.5 Data Collection

The primary source of data was semi-structured interviews with project team members. Data was collected retrospectively (between July and November 2021) as access to interview respondents was only granted after the two phases of the AISys project were complete, in July 2021. A semi-structured interview protocol was used to guide the interviews (Yin, 2014). See **Appendix D** for the semi-structured interview guide. Interview respondents were selected based on their ability to provide a detailed, first-hand account of the development and implementation of the system. At BizAI, almost all members of the AISys development team responded to our request for participation. At CityPort, most of the employees directly involved in the development and implementation of AISys responded to our request for participation. The General Manager of LogistiCluster provided his perspective of his direct involvement in the project, and the impact of the project on the transportation sector in general. Unfortunately we did not have access to other actors in the project ecosystem (shipping companies, terminal operators and rail transporters), and so the Project Manager at CityPort acted as a proxy for these groups. Interviews were conducted via video conference, recorded, and transcribed. Initial interviews lasted for an average of 60 minutes, and follow-up interviews ranged from 25-75 minutes. Internal project documentation was used to triangulate statements from interview respondents, to counter recall bias and to provide more fine-grained detail of events as they unfolded (Yin, 2014).

In addition, several sources of secondary data were also collected, including internal project documentation and reports, media articles and organizational documentation such as annual reports of the project organizations. The internal documentation and the two presentations were used to triangulate statements made by respondents and to confirm the project timeline. The AISys User Guide was used to triangulate and further understand training and information documentation provided to participating organizations Annual reports from CityPort and LogistiCluster were used to confirm the public discourse concerning the objectives and outcomes of the AISys project from the perspective of the client and the transportation sector Annual reports and strategic plans from AIFund were used to confirm the purpose and the amount of the funding from AIFund and the outcomes of the AISys project and to better understand the local AI sector in general. Press articles and press releases served to provide background information for the project context and environment, to confirm the project timeline and the impact of the project on the client, the provider and the logistics ecosystem. See **Tables 2-2 and 2-3** for details about the data collection. Throughout coding, detailed memos were made to keep track of emerging ideas (Miles *et al.*, 2013).

Table 2-2 Primary Data Collected

Total number of interviews			**16**
Total pages of transcribed interviews			**199**
Organization	**Role**	**Total minutes recorded**	**Total pages**
Client (CityPort)	Director of Innovation and Strategy (initial)	58	14
	Director of Innovation and Strategy (follow-up)	44	13
	Project Manager (initial)	57	15
	Project Manager (follow-up)	85	12
	Director of IT	57	15
Provider (BizAI)	Director of Product Management (initial)	41	11
	Director of Product Management (follow-up)	22	6
	Business team lead	53	15
	Business team lead	22	7
	Technical team lead	57	17
	Technical team lead	27	9
	Data scientist	52	15
	Senior developer 1	56	16
	Senior developer 1	21	8
	Senior developer 2	43	10
Transportation alliance (LogistiCluster)	General manager	54	16

Table 2-3 Secondary Data Collected about AIsys Project

Total pages of documentation		**518**
Document type	**Source**	**Pages**
Internal documentation		
Steering Committee presentation slides (5 presentations)	BizAI	131
Funding requests (2)	CityPort	11
Internal presentation slides	CityPort	2
Award application	CityPort	19
Publicly available documentation		
User guide	LogistiCluster	12
Annual reports (4)	CityPort	120
Annual reports and strategic plans (2)	AIFund	104
Annual reports (2)	LogistiCluster	42
Press articles and press releases (13)	Different media sources	48
Informational videos (4) (not transcribed)	CityPort website	
Presentations		
1 conference presentation (transcription)		8
1 business presentation (transcription)		21
How this data was used: The internal documentation and the two presentations were used to triangulate statements made by respondents and to confirm the project timeline. Publicly available documentation was used to triangulate and further understand training and information documentation provided to participating organizations (user guide and informational videos provided by CityPort), confirm the public discourse concerning the objectives and outcomes of the AISys project from the perspective of the client (CityPort annual reports) and the transportation sector (LogistiCluster annual reports), the purpose and the amount of the funding from AIFund and the outcomes of the AISys project (AIFund annual reports and strategic plans), and to better understand the local AI sector in general (AIFund annual reports and strategic plans). Press articles and press releases served to confirm the project timeline, the impact of the project on the client, the provider and the logistics ecosystem, and to provide additional background information and context of the project.		

The authors also benefitted from an in-depth knowledge of the overall operations and project management approach at BizAI as both authors had previously collected data on how AI projects were managed at BizAI as part of a related study (cf. Courpasson, Dany et Clegg, 2012). Seven interviews had been conducted at BizAI. These interviews lasted an average of 53 minutes for a total of 402 minutes and 165 pages of verbatim transcriptions (**Table 2-4**).

Table 2-4 Additional Interviews Conducted at BizAI

Table 4: Additional Interviews Conducted at BizAI			
Interview	**Role**	**Total minutes recorded: 402**	**Total pages: 165**
1	VP Product Delivery	56	27
2	Scientific Advisor	48	21
3	Chief Supply Chain Officer	52	21
4	Senior AI Consultant/Agile Product Owner	61	24
5	Project Team Lead	57	26
6	VP Solution Engineering	65	23
7	Agile Coach	63	23
How this data was used: These interviews were conducted prior to the AISys project. The information gained from these interviews served to provide additional information about BizAI in general, their project management approach and their approach to working with clients.			

2.4.6 Data Coding and Analysis

The case data was analyzed using analytic induction (Lewis-Beck, Bryman et Liao, 2004; Patton, 2002). During analytic induction, the researcher iterates between existing theory and case data to explain the phenomenon under study (Lapointe et Rivard, 2005; Negoita *et al.*, 2022; Patton, 2002). Analytic induction begins deductively, and in our case it began with the conceptual framework depicted in **Figure 2-1** based on coping theory. An initial set of a priori codes was developed using constructs derived from this framework, including stressors, primary appraisal of stressors, secondary appraisal of coping resources and response possibilities, coping response strategies and project outcomes; and the data was organized using these codes. Based on our initial framework, we expected both COVID-19 induced urgency and AI-related complexity to be present as sources of stress. Within each overarching construct of coping theory, each excerpt was then coded using open coding to develop first order concepts, which were then consolidated into second order categories. Through this process, four distinct stressors emerged. The trajectory of each stressor was analyzed from the team perspective: primary and secondary appraisal of the stressor and response possibilities including available resources and the coping response. For example, the short time to complete the project unsurprisingly emerged as a stressor that was appraised communally as a threat to the project by the project team (primary appraisal). The project team identified certain resources at its disposal to respond to this stressor (secondary appraisal), including the high quality of BizAI, the supplier. The coping response was to accelerate the project using various strategies and to minimize its technical risk.

This round of coding was then followed by a round of inductive coding, during which the data was further analyzed to integrate aspects of the case not clearly explained by our initial framework (Patton, 2002). During this phase, analysis focused on mapping the trajectory of each stressor, by identifying how they were appraised, and which resources and strategies were beneficial for responding to each stressor. Two coping response strategies emerged in this phase as being critical to the project's success: client responsibility for orchestration and socialization; and strategic data science overstaffing. For example, in the case of the stressor mentioned above, one of the strategies to minimize technical risk was to engage in data science overstaffing, by staffing a second data scientist on the project, and by ensuring that additional data science experts were "retained in the orbit" of the project, ready to assist if needed. The analysis also reavealed that strategically engaging in data blueprinting could benefit organizations in other contexts wanting to rapidly engage in AI projects in complex environments. The data was also coded for project outcomes, as it was important to determine that the AISys project was indeed successful. Detailed findings on project outcomes are available in **Appendix C**. Throughout coding, a coding logbook was kept to track and refer to the definitions of each of the codes to ensure consistency. NVivo (Version 12) was used to support coding and analysis.

2.5 Findings

Successfully managing a rapid AI project within a complex supply chain ecosystem requires extensive domain and technical expertise and project management skill, but also an ability to cope with stress emerging from the project. There were four main stressors the project team encountered: (1) a rapid increase in urgent demand for PPE; (2) a short time frame to complete the project; (3) suboptimal quality of existing data; and (4) supply chain complexity. While we expected AI-related complexity to be important in this case, we found that the project team made deliberate decisions early in the project to minimize the technical or algorithmic complexity related to AI. Instead, we found that AI-related stress arose primarily from the data and not the algorithms, and that complexity arose from the supply chain ecosystem. The theoretical lens of coping theory allowed us to map the primary and secondary appraisal of stressors, the coping resources available to the project team and allowed us to understand how these resources were leveraged into coping response strategies. We present below how the AISys project team coped with the project stressors.

2.5.1 Stressor 1: Rapid Increase in Urgent Demand for PPE

The first stressor the team encountered was the rapid increase in urgent demand for personal protective equipment (PPE) – primarily masks, gloves, and hand sanitizer – the only known defense against COVID-19 in early 2020. This stressor was the catalyst for the AISys project. The project team, whose membership included staff from BizAI and CityPort, appraised this stressor as an opportunity for them to work together towards a response to the threat of COVID-19 (primary appraisal): "*The context was important … the social aspect of the project, the ability to possibly save lives, was important to all of us"* (Director of IT, CityPort). See **Figure 2-5**.

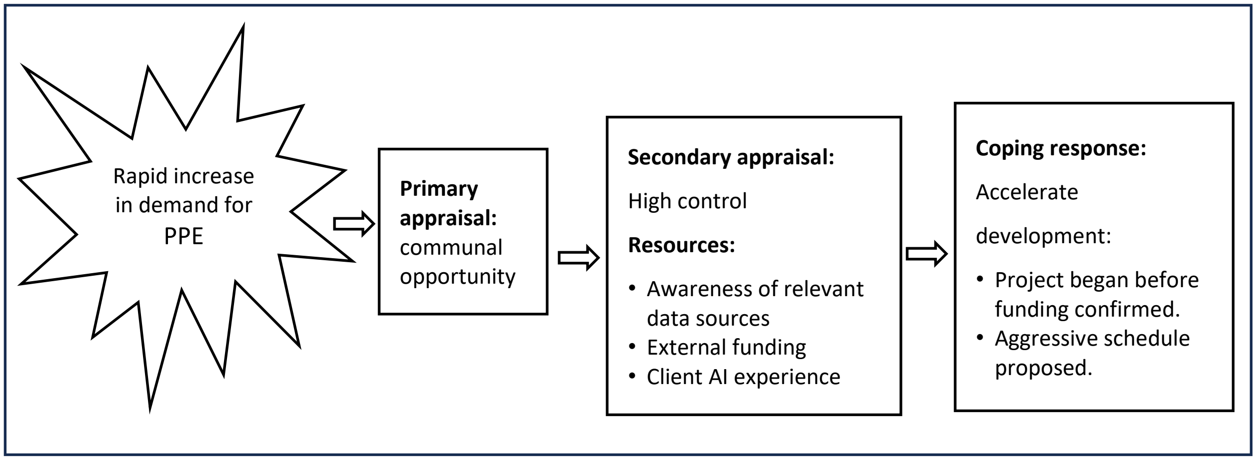

Figure 2-5 Appraisal and Response to Rapid Increase in Urgent Demand for PPE

Once the team recognized the opportunity, they assessed their communal resources and concluded they could tackle this stressor (secondary appraisal: high control). The high level of control over this stressor was appraised communally: CityPort and BizAI saw an opportunity to act together. One communal resource was available data relevant to the AISys project: the supplier, BizAI, and the client, CityPort, had conducted an AI data assessment "blueprint" for the PortOpsAI project in the fall of 2019. During this prior initiative, BizAI explored samples of the data CityPort had access to, which included the cargo manifests of incoming ships, containing descriptions of the contents of containers onboard[10]:

> *The [cargo manifests] had been evaluated during the blueprint phase [of the ground operations optimize project] so it was a data source that was already*

[10] There were several challenges with the quality of the data found in the cargo manifests, which will be covered below.

known. It was the key, the reason that we [had the go-ahead] because we knew and understood that data source. (Senior Developer 1, BizAI).

The goal of the PortOpsAI project was operational optimization in general, regardless of the contents of shipping containers, therefore the cargo manifests could have easily been dismissed by the BizAI team. However, the data blueprinting exercise for PortOpsAI was sufficiently exhaustive that the cargo manifests were noticed and examined by developers from BizAI during the blueprint for PortOpsAI and when demand for PPE rapidly increased, the critical importance of this data source came apparent for the AIsys project. Because the project team was aware of this data and understood the structure of the manifests, the AISys team could confidently propose using them for the AISys project.

In addition, CityPort had a certain degree of AI readiness, as they had experience with AI projects within their organization (a resource):

> *The other thing that helped a lot is that at CityPort, we had already done projects in AI. We were quite realistic about the expectations about an AI solution being developed so fast. That really helped us have a common vision*. (Director of Innovation CityPort).

Finally, while the project team was contemplating beginning a project, AIFund announced funding for supply chain projects that used AI to tackle the COVID-19 pandemic (a resource).

The coping response the team adopted was to accelerate development. Specifically, the project team began the project even before funding was confirmed: *"We began coding before we knew that the project would be signed [and funding confirmed] because we knew that we had a short timeline, we needed to start right away."* (Senior Developer 1, BizAI). In addition, they proposed completing the project within just 12 weeks, a timeline considered very aggressive for an AI development project. See **Appendix B** for further evidence supporting this and other project stressors.

2.5.2 Stressor 2: Short Time to Complete the Project

The second stressor the project team encountered was a short amount of time to complete the project, which was appraised as a threat (primary appraisal – see **Figure 2-6**). Completing a project in such a short time was unheard of for BizAI and CityPort and would need a lot of work, as noted by both the Director of IT at CityPort: "*The challenge was the timeline, I'll be honest, it* *was aggressive*" and the Data Scientist from BizAI: "*There was a short amount of time to do everything and that of course was not easy*." This stressor was appraised as being communal: the team recognized that the timing affected the entire project team and that they would all need to contribute to complete the project on time. Following primary appraisal, the team assessed their resources and determined that their control over the stressor was high (secondary appraisal). The most significant resource was the quality of the proposed supplier, BizAI. BizAI's staff and scientific advisors were experts in developing AI systems and in operations research. BizAI had developed a project management approach specific to AI projects and therefore had a good understanding of how long certain steps in the science and the system engineering aspects of AI development might take. In addition, BizAI had experience successfully delivering several AI projects to various clients before embarking on this one, at a time when many of their competitors were struggling, which demonstrated that their approach worked. As BizAI was directly involved in the project, their expertise and experience were considered as communal resources.

Following secondary appraisal, the project team adopted two general coping strategies in response

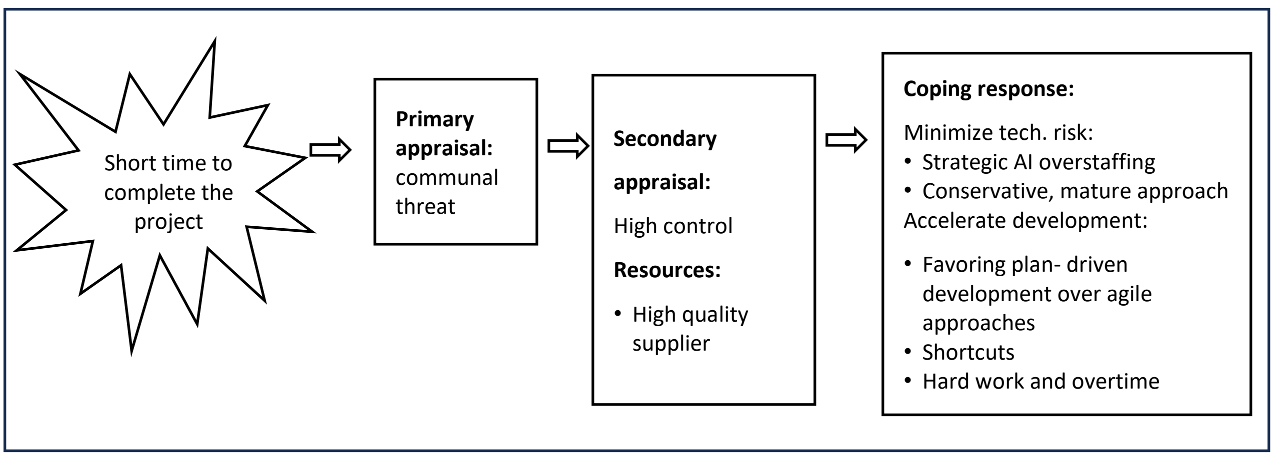

Figure 2-6 Appraisal and response to Short Time to Complete the Project

to the short time frame: minimizing the technical risk of the project and otherwise accelerating development. Technical risk was minimized through the composition of the technical team responsible for developing the algorithm and the choice of the algorithm itself. First, BizAI engaged in strategic AI overstaffing. The AISys project was deliberately staffed differently from the usual approach at BizAI. Like many AI consultancies, BizAI had several data scientists on staff as their role in creating and fine-tuning the algorithms used to find insights from data is critical for AI projects. At BizAI, project teams would typically consist of several software engineers and data engineers and one data scientist. Each team would also be assigned a scientific advisor: a seasoned academic who was up to date on academic literature relevant to the project and whose role was to advise the project team. The AISys project team included *two* data scientists and had *two* scientific advisors. Moreover, in a further departure from the normal approach at BizAI, additional staff specialized in data science were asked to "orbit around" the project and to be ready to get involved sporadically. The Technical Team Lead at BizAI explained how this helped minimize the need for onboarding of additional project team members:

> *We would try to have people orbit around the project, for example, people who already had access [to the client's infrastructure and data], who already knew the use case, without formally being on the project, just in case. We had some people who came on from outside the project to conduct data analysis for two or three weeks, just to lend a hand. This was unusual for us; it was really unique to this project.*

Technical risk was further minimized by BizAI by selecting a conservative, mature approach to developing the algorithm at the outset of the project rather than seeking advanced or cutting-edge techniques, as explained by Senior Developer 1 from BizAI:

> *With respect to the science, we knew that the science and the basic models were extremely simple, known for around 25 years, so … obviously, it was not cutting-edge research, but rather techniques that have been proven, and we knew we could move ahead with those techniques, so that considerably de-risked the scientific aspect of the project.*

The second coping response was to accelerate project development, and one way this was done was through primarily relying on a phased approach to development, rather than agile, iterative approaches. Work was organized in two-week sprints as is recommended by agile methods, but the overall project plan and schedule played a more important role than usual in guiding decision-making. Each phase was precisely planned, and scope change requests were highly scrutinized with only the most important ones being incorporated. Another way was by taking shortcuts, specifically by beginning before having full specifications for the project or even reflecting on key aspects of the final product such as the user experience or user interface, as noted by Senior Developer 1 from BizAI:

> *It was rather particular as a project considering we had 10 weeks…so in those circumstances what happened is we began to work on the project before having complete specifications … we agreed on the scientific aspects that would be the*

core of the project, but the uncertainties related to the user interface and the UX in general, that reflection hadn't happened yet.

Finally, the team members engaged in hard work and overtime. These three strategies could be considered communal, in that they were enacted by the team and for the benefit of the project team.

2.5.3 Stressor 3: Suboptimal Data Quality

Data quality emerged as a stressor from the project data, but a structured approach to analyzing data quality drawn from academic literature assisted in the analysis. The four dimensions we used to analyze challenges with data quality are intrinsic data quality (data accuracy), contextual data quality (data latency), data accessibility quality and representational data quality(Wang et Strong, 1996). Challenges with all four dimensions of data quality were appraised as a threat (primary appraisal – see **Figure 2-7**) by the project team: data is a critical ingredient for AI, and problems with its quality can compromise the functioning and the output of an AI system. Improving the quality of the data needed by AISys was addressed through socialization, or encouraging behavior change through education of project partners.

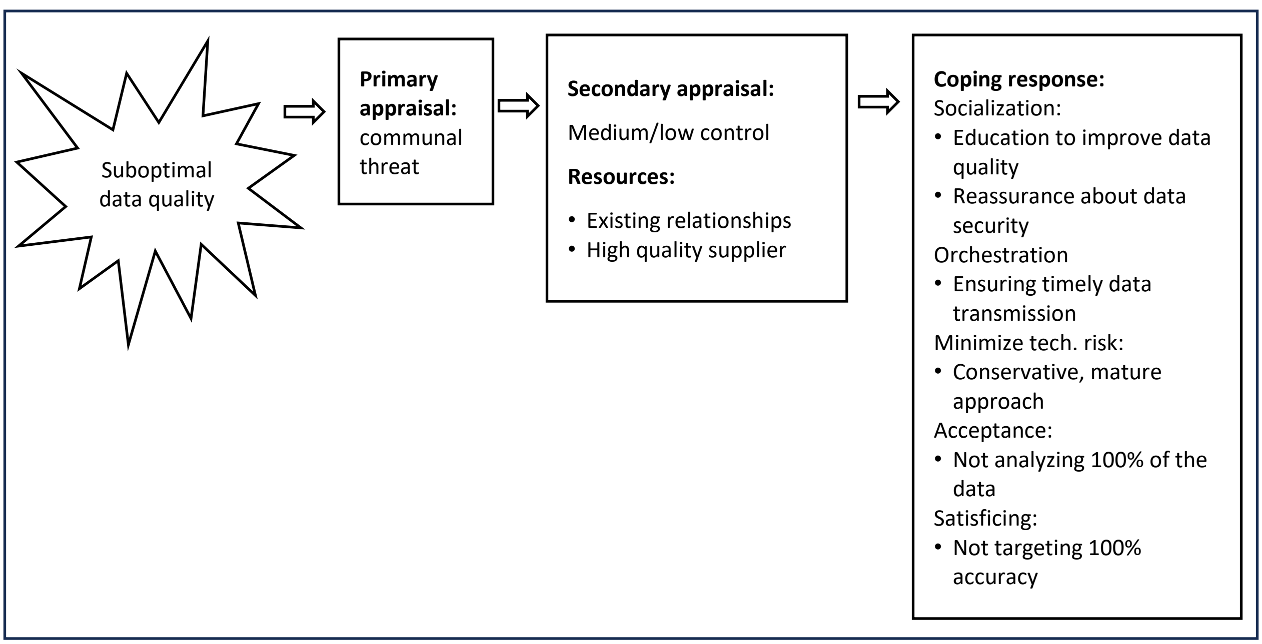

Figure 2-7 Appraisal and response to Suboptimal Data Quality

2.5.3.1 Intrinsic data quality (data accuracy)

The primary appraisal of intrinsic data quality, particularly data accuracy, was appraised as a threat was due to errors in item descriptions or reference codes in the cargo manifests; the wrong data sometimes being transmitted; incomplete cargo manifests being transmitted; and data quality having been compromisse during preprocessing by CityPort. BizAI had medium control over their response to challenges related to data accuracy (secondary appraisal). Three resources allowed the team to address this stressor: CityPort benefited from existing relationships with shipping companies; AISys was a high-quality supplier; and the data blueprint for PortOpsAI provided the BizAI team with an understanding of the data to be used for AISys.

There were two main response strategies to this stressor. The first was for CityPort to engage in socialization activities with the shipping companies, freight forwarders and importers active in the local ecosystem. This involved explaining to these organizations why and how accurate cargo manifests directly impacted the ability of AISys to identify and fast track critical cargo and providing clear instructions to shipping companies on how to improve the cargo manifests. The Product Manager from BizAI explained: "*What we wanted to socialize was … that the data must be properly labeled … described with the correct codes.*" The project team provided these companies with the list of codes for priority items and instructions on how to complete cargo manifests to ensure that priority items were properly identified. The list and instructions were included in a newly created AISys user guide, available on the CityPort and LogistiCluster websites.

The team also used the same response strategy mentioned above of minimizing technical risk by proposing a mature algorithm that required minimal training and was relatively robust to issues with the data, favoring system reliability over increased potential accuracy.

2.5.3.2 Contextual data quality (data latency and completeness)

Data latency and completeness were appraised as a threat (primary appraisal). In the early days of the project, data was often transmitted to CityPort after a ship had arrived at the port and had been unloaded. Similarly, many of the cargo manifests were not complete. The project team had medium control over data latency (secondary appraisal) because of existing relationships with the shipping companies (a resource), which made it easier for CityPort to approach these companies. The response was for CityPort to engage in socialization, this time to change the shipping companies' data transmission behavior. CityPort explained to the shipping companies the negative impact late data transmission had on AISys' ability to identify and subsequently fast track critical containers, as explained by the Project Manager at CityPort:

> *We asked [the shipping lines], 'Can you send [the manifests] a bit earlier? That will really help us identify containers in advance, we will be able to speed everything up.' And two shipping lines changed their process, and we received the [manifests] six or seven days in advance in some cases, compared to 24 hours late before.*

However, the project team had medium control over data completeness, as the NLP algorithm used could compensate for some, but not all, of the missing data. The response was therefore acceptance: the BizAI team clearly informed the client (CityPort) that data was missing from at least 15% of cargo manifests, and this would impact the accuracy of the algorithm's predictions.

2.5.3.3 Data accessibility quality

Legal and security requirements governing data sharing among local supply chain ecosystem partners, as well as competing business interests, limited data accessibility for the AISys project. This was appraised as a threat by the project team (primary appraisal). However, due to existing relationships between CityPort and local supply chain ecosystem organizations in the form of pre-existing data transfer agreements, the project team determined that they had a medium level of control over the accessibility of data necessary for AISys (secondary appraisal). To ensure continued access to this data, the client (CityPort) explained to importers, freight forwarders and shippers that the system was designed such that no information describing the contents of a container would be available to other organizations in the supply chain beyond the label "priority." These explanations were accompanied by formal legal agreements. This socialization activity served to reassure these organizations that clearly labeling the contents of their containers would not compromise their business interests (coping response).

However, despite these socialization efforts, a percentage of containers could not be identified by the system. Therefore, the response to this stressor included accepting that the solution would not be perfect: for 15% of the cargo, descriptions were not available and could not be interpreted using other information.

2.5.3.4 Representational data quality

With respect to representational data quality, the level of granularity of descriptions of items in cargo manifests was appraised as a threat (primary appraisal). Item descriptions were based on an international classification system called Harmonized System (HS) codes that is updated every five to 10 years, and the level of detail and granularity did not necessarily reflect the needs driven by the COVID-19 pandemic. For example, the HS code associated with alcohol-based hand sanitizer was for a general category of pesticides and disinfectants. The concentration of the solution, and the size of the container, were not necessarily indicated. Other items might have a very specific code. The variability of the item descriptions and codes complicated the development of a search list, as explained by the Product Manager at BizAI:

> *[One] challenge, if I come back to this list of 90 [priority items provided by the government], the technical side needs to understand that this list isn't uniform. In the baseline of items we were looking for, there could be items at a very high level, like alcohol, or a chemical product that was extremely precise with a quantity in mL, like 10 mL of X, so we had items at various levels of granularity, and we had to determine how to prioritize them.*

In addition, the data from multiple sources was not always consistent. The project team determined they had low control over representational data quality (secondary appraisal), as they could not change the classification system or the documentation system from each source. The response was therefore satisficing: in order to complete the project rapidly, BizAI decided to not aim for 100% accuracy and communicated this information to internal and external stakeholders.

2.5.4 Stressor 4: Supply Chain Complexity

Supply chain ecosystems are complex, with multiple elements that interact in a dynamic and unpredictable fashion. Three dimensions of the complexity of the AISys ecosystem were sources of stress and appraised communally as threats to the project: the need for alignment among diverse organizations; the heterogeneity in technical maturity of the organizations impacted by AISys; and the fact that the developers at BizAI only had indirect access to the system end users. The primary coping responses to address this stressor were orchestration and socialization of project partners, as explained below. See **Figure 2-8**.

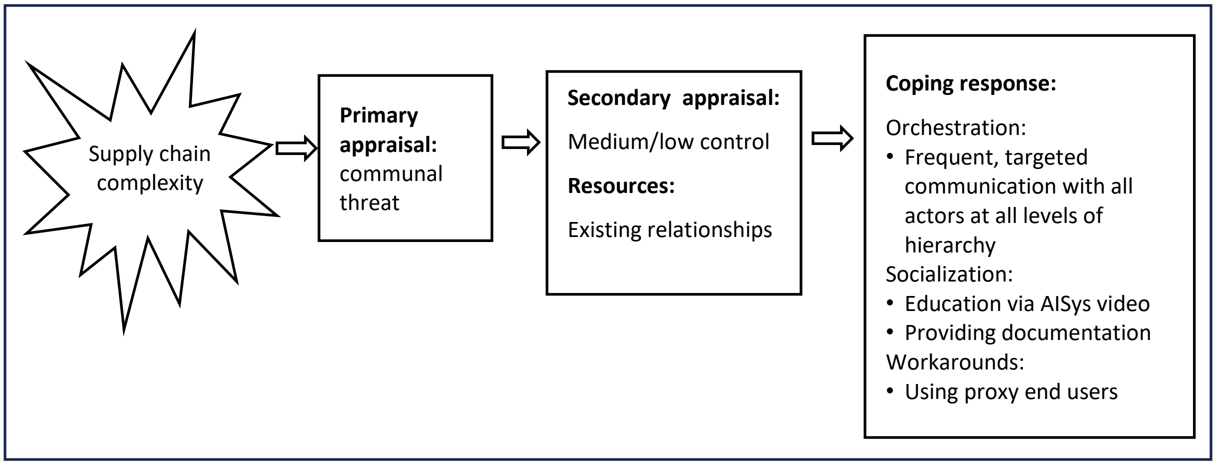

Figure 2-8 Appraisal and response to Supply Chain Complexity

2.5.4.1 Need for alignment among diverse organizations

The need for alignment among the diverse organizations involved in the project was appraised as a threat (primary appraisal). The project actively involved about 15 different organizations and impacted many more, and the success of the project depended on the alignment of the interests, operations, and information systems of these organizations. The alignment such a diversity of actors was mentioned by several respondents as being a challenge for the project. Furthermore, the operational priorities and issues of project partners were not always in line with AISys' priorities. For example, rail operations and schedules dictated when a train would depart, regardless of the presence of critical cargo; one terminal operator was undergoing a website migration at the time of AISys; and operational disruptions affecting many project organizations occurred at various points in the project.

The project team determined they had medium control over the alignment of core project organizations (secondary appraisal), due to existing relationships (a resource). Through frequent contact with the terminal operators, the Project Manager at CityPort had developed a deep understanding of the operators' challenges and their operational reality. Furthermore, CityPort was a member of LogistiCluster through which they could access other actors, as explained by the General Manager of LogistiCluster: "*We think that the involvement of LogistiCluster, having this cluster in place since 2013, having these players, including the trucking community, present, it was a success factor for this projec*t." The team therefore relied on CityPort to engage in orchestration of the core project organizations (response) by leveraging these relationships. Orchestration activities broadly referred to actions to coordinate and align participating organizations in the AISys project. Orchestration involved "*aligning the actors, the terminal* *operators, the rail lines, the six shipping lines, the [many many] trucking lines [through] major and frequent… communication about the project*" (Product Manager at BizAI). The project team approached project organizations and the local supply chain ecosystem strategically, determining in advance who to approach, what messages to share and how to share them. CityPort team members communicated directly with different levels of hierarchy within other organizations, as explained by the CityPort Project Manager:

> *We started by defining the strategy, how we would approach the top management at our partners to engage the entire enterprise, and then how we planned to engage people at an operational level so the daily work can be beneficial and contribute to the velocity of the project, and then how we would obtain feedback from them. It's something we asked ourselves throughout the project.*

CityPort also engaged in socialization tactics, to encourage project partners to change their behaviour and increase their collaboration to maximize the effectiveness of AISys. One socialization tactic was to produce an informative video which explained the purpose of the AISys project and the role of the different actors in fast-tracking critical cargo, and provided a non-technical explanation of how the NLP approach used in AISys was designed to work. This video was shared with project partners to educate them and explain the impact their participation could have on the AISys project.

However, the project team determined they had low control over certain operational priorities of different actors (secondary appraisal). Their coping response therefore was satisficing. CityPort engaged actively in orchestration and socialization activities to emphasize the importance of AISys and the role different actors needed to play to ensure its success, hoping it was sufficient to influence behaviour of broader project organizations.

2.5.4.2 Heterogeneity in technological maturity

The heterogeneity in technological maturity of the actors in the local supply chain ecosystem was appraised as a threat by the project team (primary appraisal). Within the local supply chain ecosystem, many large companies used advanced information systems, whereas some of the trucking companies still operated using fax machines. The project team was unsure companies with low IT maturity would accept and adopt AISys. The team determined they had medium control over core project organizations (secondary appraisal): while the project team could not change the technological maturity level of organizations within their ecosystem, they could educate and support them. CityPort had conducted AI projects prior to AISys and were familiar with this type of technology (a resource). The coping response was for the client (CityPort) to engage in the socialization of project partners using the video mentioned above, and by providing training and documentation. The explanation of the technology behind AISys in the video helped demystify the system's functioning and clarify the impact their participation could have on the goal of fast-tracking critical cargo. A user guide and accompanying FAQ was developed by the project team, shared by LogistiCargo and disseminated via the CityPort website. This documentation explained to ground transportation companies how to interpret and use the output from AISys. These two tools were seen as particularly important for actors with lower levels of technological maturity. To increase the potential effectiveness of socialization with respect to increasing understanding of AI within the ecosystem, the CityPort Project Manager spent time during the project to learn about NLP and AI applications in supply chain operations to be better able to explain the project to both internal and external stakeholders.

2.5.4.3 Indirect access to end users

For various reasons, the supplier, BizAI, did not have direct access to the people who acted on the system output, the longshore workers responsible for unloading ships and stacking containers in a way that would optimize the retrieval of critical cargo. Instead, they had to work through the CityPort Project Manager. This indirect access was appraised as a threat (primary appraisal). This meant they could not influence their adoption of the system nor predict their reaction to the system. The project team determined they had low control over this stressor (secondary appraisal), as explained by the Technical Team Lead at BizAI:

> *We had the impression that if we had spoken to the operators, we could maybe have better understood what the real levers they had to encourage the COVID containers to leave the port. Because in reality, other than giving them the information in a little file, we didn't know what else we could do. That was a major issue, particularly with the terminal operators.*

Their coping response was to use workarounds: instead of working directly with the terminal operators, the project team gained insight into their operations via the Project Manager at CityPort who, in addition to his other responsibilities, had developed a deep understanding of terminal operations and could represent the terminal operators' interests to a certain extent.

2.6 Theoretical Development

Our analysis using a team-level coping lens allowed us to map the project team's appraisal of four key stressors with their secondary appraisal of resources and their adoption of coping strategies. While several coping resources and response strategies were identified in the analysis, three key insights emerged which enrich our understanding of how an organization can manage a rapid AI project in a complex supply chain ecosystem. The first insight is the potential impact of socialization and orchestration when conducting an AI project within a complex supply chain ecosystem. In this study, these actions addressed both suboptimal data quality and the alignment of diverse actors involved in the project, stressors which can be expected in AI projects in complex environments. Orchestration activities focused on maintaining, leveraging, and further developing relationships among the broader project organizations, and coordinating the actions and activities of all participating organizations. Socialization involved taking specific actions designed to change the behavior of shipping companies, freight forwarders and importers to improve the accuracy, latency, and availability of the data critical to AISys, and educating all actors impacted by the AISys project about the technology driving the system and their role in maximizing its effectiveness.

The second insight was the use of strategic data science overstaffing. This technique was enacted by the project team in two ways: explicitly increasing the data science experts staffed to the project and having other employees who were not officially assigned to the project "retained in the orbit" of the project. These individuals had both knowledge of the project context and specific related expertise and were ready to assist when needed, which helped the AISys team complete the project rapidly.

In addition to these two strategies, the findings also indicate that the data exploration, or "blueprint" phase of an AI project can offer strategic benefits beyond the project for which it was intended. This suggests that in certain circumstances organizations can benefit from engaging in regular, strategic blueprinting that can feed multiple projects instead of only using this phase to begin a single AI project. In the AISys project, the knowledge gained during blueprinting served as a resource to cope with the rapid increase in urgent demand for PPE that catalyzed the project, and stress induced by limitations in intrinsic data quality.

2.6.1 Client Responsibility for Socialization and Orchestration Activities

Our analysis of the AISys project suggests that the project team's success was at least in part driven by the client taking on the responsibilities of socialization and orchestration in response to suboptimal data quality and the complexity of the environment. These actions contributed to the on-time delivery of a working system, and to the strategic success for the ecosystem.

This demonstrates the role socialization can have in improving multiple aspects of data quality when managing AI projects involving many organizations and the role it. AI projects require high quality data in sufficient quantity to be effective (Vial *et al.*, 2021). Projects that aim to influence operations in near real-time need this data to arrive prior to the operations in question being enacted (Chen *et al.*, 2021). The AISys project required high-quality data from multiple sources to be transmitted to CityPort four days before a ship arrived, and at the project outset, the data quality was sub-optimal, not all data was available and often the data arrived after a ship had already been unloaded. Socialization with upstream supply chain organizations involved explaining their role in ensuring the data that would be processed by AISys was transmitted sufficiently early to ensure planning of ground operations, and that the data was of sufficiently high quality. Through active socialization of the organizations providing the data, the project team was able to increase the overall quality of the data to be processed by AISys, increase the precision of the output, and expedite more critical containers. Socialization of downstream organizations responsible for the physical movement of containers involved educating these organizations on how to use the output of AISys to plan their operations. It also involved increasing their overall understanding of AI by using an informative video, an FAQ and documentation made readily available to explain the technology behind AISys in clear terms. This study therefore demonstrated that socialization can bring organizations in a complex supply chain ecosystem to the minimal level of understanding of AI required to effectively participate in an AI project.

Socialization alone may not have been sufficient, however, because the multiple organizations involved in this project needed to be aligned. Orchestration involves sharing the strategic vision of the project, creating buy-in, connecting key network actors and favoring activites that maintain the coherence and quality of the project from beginning to end (Paquin et Howard-Grenville, 2013; Roehrich *et al.*, 2023). CityPort, through their position in the local supply chain network, was the ideal organization to act as chief orchestrator, and in this role, their orchestration activities involved maintaining and leveraging existing relationships among actors and ensuring continued interorganizational system and data integration. The role of both socialization and orchestration activities for AI projects in complex supply chain ecosystems is captured in the first proposition that emerges from this study:

Proposition 1a: For AI projects that take place within a complex ecosystem, involve multiple actors with uneven levels of AI maturity and where data quality is insufficient, it is important for clients to engage in socialization activities with all actors involved in the project.

Proposition 1b: The effectiveness of these socialization activities increases when strong relationships have been built and are maintained among actors involved in the project.

2.6.2 Strategic Data Science Overstaffing

The data from the AIsys project suggest that the project's success may have also been due in part to strategic data science overstaffing. Interestingly, the project team decided explicitly to ensure that the resource that is the scarcest (i.e., data science expertise) is the one that needed to be "overstaffed." BizAI engaged in two overstaffing approaches: explicitly assigning extra experts to the project and ensuring that additional experts were "retained in the orbit" of the project to assist if needed. BizAI's decision to increase the presence and involvement of these experts was driven by the need to complete the project rapidly, but it also helped to address the complex nature of the project.

Overstaffing is one way to create slack resources. Slack is defined as an excess of resources available to an organization but not exploited at a given time and can be conceptualized as monetary resources, organizational capacity (e.g. for production) and organizational capabilities (e.g. staff skills and expertise) (Dolmans *et al.*, 2014). In innovation and entrepreneurship literature slack resources have been demonstrated to be positively related to firm performance (Daniel *et al.*, 2004).

Data scientists are professionals with highly specialized skills, and at the time of the AISys project, were scarce and in high demand (Thomas H Davenport *et al.*, 2022). Despite their scarcity and specialized skillset, BizAI decided to increase their capacity for this project by assigning an extra data scientist and scientific advisor, and also by asking extra data scientists and data engineers to "orbit around the project," or stay informally involved and be kept aware of the project environment, developments and needs so they could rapidly assist if needed. These additional experts were privy to the challenges encountered by the project team and how they were overcome, the technical decisions made on the project and the project environment in general.

This considerably reduced the time required for onboarding extra data science staff and increased their ability to offer support when called upon. This insight leads to the second proposition of this study:

Proposition 2: Strategic data science overstaffing on AI projects is a beneficial coping resource when a project is urgent, when an AI system is developed within a complex ecosystem, or when roles needed on the project such as data scientists are otherwise scarce and hard to quickly obtain and integrate into the project.

2.6.3 Blueprinting to Serve a Portfolio Approach to AI Projects

The findings suggest that the success of the AISys project may have been partly attributed to the tacit knowledge the project team developed about the data during a blueprint conducted of CityPort's data for a previous, separate project, PortOpsAI. Given the urgency of the AISys project and the complexity of its ecosystem and associated data, the insight gained during this previous blueprint was a key resource to cope with limitations in data quality, and a key enabler for the project team's ability to confidently propose a project that was feasible within a short time frame.

Many AI projects begin with data assessment, or a blueprint (Vial *et al.*, 2023). This project practice allows the development team to understand an organization's data and infrastructure in connection with a proposed AI project. The blueprint phase generally ends with a decision to go or not go ahead with the AI project. In this case, the tacit knowledge the project team developed about the available data during the PortOpsAI blueprint proved vital for identifying the data required for AISys. The potential usefulness of data describing container contents was serendipitously noticed by one of the software engineers on the PortOpsAI project team. Its discovery during the blueprint phase of another unrelated project suggests that a change in how the blueprint phase is viewed and conducted could benefit other organizations in the future.

The ability to use this unexpected data source for an unplanned project demonstrates that instead of a project-level activity, "blueprinting" could be a strategic activity. That is, it could be structured as a regular exercise that organizations engage in, serving to improve organizational understanding of their data in general, and to identify potential future AI projects instead of being tied to one specific project. The results of open-minded, generic data exploration can be a useful resource for organizations wanting to initiate a portfolio of AI projects, and when the advantage conferred by the ability to quickly respond to changing market condition outweighs the potential cost of a comprehensive data assessment. Making the blueprint a strategic, rather than a project, activity would change the blueprint-to-project relationship from one-to-one to one-to-many. This specific recommendation adds to the extant literature on managing urgent projects, which focuses primarily on general project acceleration techniques(Ellwood *et al.*, 2017; Wearne *et al.*, 2014), but less on strategically creating the ability to initiate meaningful projects rapidly. This leads to the third proposition:

Proposition 3: For companies seeking to deliver a portfolio of AI projects and to be ready to rapidly respond to a specific business need, positioning AI blueprinting as a periodic strategic activity rather than a project activity should increase speed of delivering an AI project because it can help build a key coping resource.

2.7 Discussion

This study examined how a project team comprised of representatives of three organizations managed a rapid AI project in a complex supply chain ecosystem. Using the lens of team-level coping theory, we analyzed interview data and project documentation to understand which stressors emerged during the project and how the project team coped with each of them. The findings indicated that the project team did appear to appraise stressors at the team level, draw on team level coping resources when available, and employ team level coping strategies to address the stressors. At times, coping strategies involved leveraging available resources, or, when no coping resources were available, the project team engaged in satisficing or adopted workarounds. Our analysis also uncovered coping resources and strategies specific to managing rapid AI projects in complex supply chain ecosystems, including three novel insights. Drawing on the findings and insights from this study, we now outline three implications for research and practice on managing certain types of AI projects.

2.7.1 The role of socialization in addressing low data quality in AI projects

Orchestration and coordination are well known as techniques for managing projects in contexts where multiple stakeholders are involved, such as supply chains (Oliveira *et al.*, 2017; Roehrich *et al.*, 2023). These structural techniques focus on how the project is organized. However, AI projects in supply chain like AISys require high quality data from multiple stakeholders, and orchestration and coordination do not speak specifically to enhancing data quality. This study brings to light a third technique that can be beneficial for multi-organizational AI projects, that of socialization, or specific actions intended to modify the behavior of other organizations. Socialization emerged in this study as an effective strategy for increasing the overall quality of the data analyzed by AISys.

Previous literature examining the role of socialization in large projects notes that socialization can be beneficial for improving relationships among actors (Aaltonen et Turkulainen, 2018). Just like orchestration and coordination mechanisms can favor effective collaboration among organizations in large projects (Oliveira *et al.*, 2017; Roehrich *et al.*, 2023), socialization can also have an impact on data quality for supply chain AI projects (S. Camarena, 2022). Future research could examine socialization activities in AI projects in greater detail and in different types of multi-organization projects, to determine which activities are most effective in increasing data quality, what other effects it might have on the outcome of AI projects, and in which contexts socialization is particularly effective.

2.7.2 "Retaining in orbit" to increase availability of specialized resources

AI projects are almost always team endeavors. Extant research focuses on types of expertise of team members, suggesting that AI project teams should have fixed, multidisciplinary teams with different types of expertise because this approach helps ensure that a project meets both business and technical goals (Fountaine, McCarthy et Saleh, 2019; Lou *et al.*, 2021; Vial *et al.*, 2023). At the organizational level, slack resources – including additional workers and expertise beyond what is minimally required – can have a positive effect on performance in innovation (Daniel *et al.*, 2004). The addition of extra data science experts on the AISys project reflects these recommendations. However, neither recommendation explains the specific practice of "retaining in orbit" observed in the AISys project, used to rapidly integrate additional expertise midway through the project. Onboarding of new members of a software development team involves social and technical aspects and can take time to conduct properly (Gregory *et al.*, 2022). One reason cited by the project team leaders that "retaining in orbit" was beneficial for the AISys project is that it reduced time spent on onboarding new team members mid-way through the project. This suggests that retaining additional specialists in the project orbit may be an effective strategy to allow for rapid integration of specialized expertise in an AI project. The findings of this study suggest that for an AI project in a complex supply chain ecosystem, onboarding must also include developing an understanding of the project environment, therefore making "retaining in orbit" even more beneficial in these contexts. Future research could investigate whether "retaining in orbit" happens in other contexts, how and why it is used and to what effects for the project and the organizations involved.

2.7.3 Blueprinting as a strategic, not a project, activity in certain contexts

New product development in many industries, including AI development, is often organized using a stage-gate approach which helps reduce risk by only proceeding with projects that display initial promise and viability (Cooper, 2019). This is the same justification for beginning an AI project with a blueprint (Vial *et al.*, 2023). However, the AISys project revealed that a blueprint, or data assessment for an AI project could serve purposes other than the initial stage of one AI project through the development of tacit knowledge about available data. The serendipitous noticing of cargo descriptions during the blueprint for the PortOpsAI project and remembering of this information enabled the project team to use this data for a subsequent successful project, AISys.

Identifying opportunities and reducing bottlenecks are seen as two key strategic activities for AI project management, particularly when the goal is to plan for a portfolio of AI projects (Davenport et Ronanki, 2018). Conducting regular, general AI blueprints – during which tacit knowledge is developed of both expected and unexpected aspects of data and systems – to inform overall organizational AI strategy could help serve this objective. Future research could examine how organizations currently approach the early phases of their AI projects to determine how to best conduct strategic data blueprinting.

2.8 Conclusion

This study aimed to advance our understanding of managing rapid AI projects in a complex supply chain ecosystem. We applied team-level coping theory as a lens to analyze the case of an AI project conducted at a major international port during the early days of the COVID-19 pandemic and uncovered two novel important coping resources and one novel important coping strategy. We thus provide directions for future research in three areas: better understanding the effects of socialization and orchestration activities on improving data quality, technical maturity and inter-organizational collaboration; how to engage in strategic data science overstaffing; and how to strategically assess an organization's data for planning a portfolio of AI projects in complex environments.

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Chapter 3
How Organizations Navigate AI Implementation: An Interdisciplinary Qualitative Meta-Synthesis of Case Studies

Abstract

Recent advances in artificial intelligence (AI) have made systems that use these techniques increasingly accessible to a wide variety of organizations. However, these systems must be implemented for them to bring value to organizations. While much is known about development and implementation of information systems in general, less is known about development and implementation of AI systems. These systems have distinguishing characteristics – they are often inscrutable, data-dependent, unpredictable, and designed to make decisions or act autonomously – and how these characteristics influence AI development and implementation is not fully understood. We conduct a qualitative meta-synthesis of published case studies of 12 AI implementation projects to uncover how organizations successfully implement these systems. We find that the characteristics of AI impact development and implementation in many ways, requiring distinct theoretical explanations for management of AI development and implementation; that organizations use various tactics and approaches to manage AI development and implementation; and that these tactics can help address the challenges posed by AI systems to enable organizations to gain value from these systems. Furthermore, we find that knowledge brokers involved in an AI-enabled workflow help address the inscrutability of AI systems through interpretation and knowledge translation work; that in certain situations, actively black-boxing the technology and focusing on performance can be an effective strategy to overcome limited interpretability of AI systems; that careful dataset curation throughout an AI project's lifecycle helps reduce the impact of challenges arising from learning-driven data dependency; and that actively requesting employee feedback can identify ways in which an AI system may negatively impact an organization.

3.1 Introduction

Recent advances in artificial intelligence (AI), defined as "*the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems"* (Berente *et al*., 2021 : 1435) have made systems that use these techniques increasingly accessible to a wide variety of organizations (Brynjolfsson *et al.*, 2017). Due to these advances in AI, organizations have found applications for AI-based systems in fields such as health care (Reis *et al.*, 2020), public services (Rinta-Kahila *et al.*, 2022) and human resources (van den Broek *et al.*, 2021) to name but a few. Most current AI systems apply machine learning (ML), a set of techniques that combine both data classification and pattern identification through learning (Burrell, 2016). However, with any information system, it is only once the system is implemented and in use in an organization that the outcomes of system implementation – positive or negative – become clear, and that an organization can reap benefits from the system.

System implementation is the initial installation of a new software product and marks the period when organizations can begin to gain value from these systems (Markus et Tanis, 2000; Whiteaker, 2000). AI implementation appears to pose significant challenges to organizations (Lee *et al.*, 2023): some are able to successfully implement AI systems (Asatiani *et al.*, 2021; Golovianko *et al.*, 2022; Sandhu *et al.*, 2020; van den Broek *et al.*, 2021), while others struggle with implementation and may even abandon a system altogether (e.g., Reis *et al.*, 2020). One survey suggested that most ML models that are developed have trouble making it out of the lab, and do not end up being implemented, limiting organizations from reaping their potential benefits (Davenport et Bean, 2022). To determine how organizations can gain value from their AI investments, it is important to understand the ML implementation process and what factors may contribute to systems being successfully implemented or failing to meet their objectives.

Extant research on IS development and implementation can inform our understanding of AI development implementation in part. For example, issues that arise during information system development and implementation can impact the ability of organizations to gain value from these systems (e.g., Bala et Venkatesh, 2016; Rivard *et al.*, 2012). However, the characteristics specific to current AI systems make them different from other types of IS in significant ways, such that the extent to which this research fully applies to AI systems is unknown. First, AI systems are often inscrutable, making it often impossible to fully understand and explain how they work (Berente *et al.*, 2021; Burrell, 2016; Schuetz *et al.*, 2020). Second, because AI systems are trained to identify patterns in data, not follow deterministic code, they require large quantities of sufficiently high-quality data. Third, by their nature, AI systems learn and adapt over time. As a result, their output is often unknowable *a priori*, and their impact may only be fully appreciated once the system is in use (Berente *et al.*, 2021; Reis *et al.*, 2020). Fourth, the ability of many AI systems to operate autonomously or with limited human intervention changes the dynamics of user-system relationships (Baird et Maruping, 2021; Berente *et al.*, 2021; Schuetz *et al.*, 2020).

These characteristics may impact the implementation process, resulting in user and organizational reactions and impacts throughout implementation that are different from those to other types of IS (Venkatesh, 2022).

This study therefore seeks to answer the research question *How do organizations navigate AI system implementation, moving from development through to widespread organizational use (or abandonment)?* To answer this question, we propose a meta-synthesis of qualitative case studies that study organizational implementation of AI-based systems. This method is useful for understanding and explaining complex interventions such as AI implementation as it considers the context surrounding the intervention (Hoon, 2013; Paré *et al.*, 2015). Previous systematic literature reviews have identified challenges and opportunities for AI in organizations and identified some solutions that may be able to address these challenges (e.g., Enholm *et al.*, 2022; Lee *et al.*, 2023; Paleyes, Urma et Lawrence, 2022). These reviews all extract challenges and opportunities from a combination of empirical and conceptual studies and literature reviews, but as they do not examine the process of development and implementation in detail (**see section 3.3 - Method**), they fall short of analyzing important nuances in the implementation process that can explain how AI implementation can be managed.

This study makes three contributions. The first is a thorough review and synthesis of 12 cases of AI system development and implementation which uncovers the ways in which the implementation of these systems is managed. These empirically grounded insights provide improved understanding for practitioners on how AI development and implementation unfolds and can help structure future theorization about this process (Agerfalk et Karlsson, 2020). The second contribution is a detailed examination via a broad selection of cases across multiple contexts of how the differences between implementation of AI systems and other types of IS are driven by certain characteristics of AI. This detailed account can help researchers and practitioners better understand the role played by the characteristics of AI systems during their development and implementation. The third contribution is an explanation of how specific practices can be adopted during development and implementation of AI systems to address the challenges stemming from the characteristics of AI. These include tactics such as encouraging AI and data literacy of non-technical employees to address inscrutability of AI systems and improve data quality and integrating knowledge brokers to improve interpretability of AI systems. The identification and explanation of these constructs is an important theoretical building block (Shepherd *et al.*, 2017) in future theorizing of AI development and implementation The analysis presented in this study, which is grounded in empirical evidence and supported by theoretical arguments, helps practitioners and researchers better understand the relationship between challenges arising from AI and specific practices adopted during development and implementation.

In the next section, we review the literature on AI development and implementation, and characteristics of AI systems. Next, we present our methodology and describe our search strategy. The findings from the meta-synthesis are presented and then are analyzed and discussed. We conclude with suggestions for future research.

3.2 Literature Review

3.2.1 AI System Development and Implementation

As AI is a type of software, AI development and implementation were inspired by software development and implementation methods, which generally follow either an iterative, agile approach; a phased, sequential approach; or a hybrid of the two. Development and implementation of an AI system generally takes place in several phases (De Silva et Alahakoon, 2022; Vial *et al.*, 2023; Wrobel, Dietzmann et Alt, 2025). *Ideation* involves the strategic decision-making of if and where to include AI within an organization. The *feasibility assessment* involves assessing organizational data, evaluating potential computational techniques available, and system capabilities. Bespoke systems are often initially developed as a *proof of concept* using historical data, followed by *a minimum viable product* using live data. Users are invited to test preliminary versions of the system, and their feedback is incorporated into subsequent iterations (van den Broek et al., 2021; Vial et al., 2023). Implementation of existing systems requires training the model on local historical data and then testing with live data. In both cases, when a model proves useful for an organization, it can be *deployed*, or connected to existing data streams and systems, and its output can be *integrated* into organizational operations (Vial *et al.*, 2023). This development approach is rarely purely sequential, rather, development teams often iterate between phases. For example, if a proof of concept is unsuccessful, teams will adjust parts of the system and conduct a new feasibility assessment, or if there are significant differences between the minimum viable product and the proof of concept, the team will return to the proof-of-concept phase.

There are some ways in which the development and implementation of AI differ from that of other types of information systems. First, specific types of user and customer collaboration help favor the successful development and implementation of AI. Many AI-based systems are designed to codify the knowledge and expertise of subject-matter experts, knowledge rarely possessed by the development team (Redman, 2019). AI development therefore requires recursive involvement of subject-matter experts – who may or may not be the end users – to determine what types of system outputs are useful for an organization, and what types of data input are necessary to generate these outputs (Gronsund *et al.*, 2020). Second, pilot tests and demonstrations of iterations of systems are crucial for AI development, as they provide an opportunity for end-users to understand how the proposed system will operate and what kind of output it will provide (Gronsund *et al.*, 2020; Reis *et al.*, 2020; van den Broek *et al.*, 2021). Third, because AI systems are designed to evolve as the input data evolves, vigilance is required at the time of deployment to ensure the system performs similarly on live data as it did during the proof-of-concept phase (Kreuzberger *et al.*, 2023).

Like all system implementations, implementing AI benefits from top management support, a strategic vision, clear understanding of potential return on investment, and appropriate change management (Lee *et al.*, 2023). Additional barriers and challenges specific to ML include a lack of understanding of the business potential of AI, a lack of confidence in AI-generated predictions, a lack of understanding of the technical aspects of AI, a lack of skills for industrialization, and a lack of quality data (Reis *et al.*, 2020). In addition, there may be ethical and legal barriers to the implementation of AI (Lee *et al.*, 2023). The potential impacts of AI on users and other stakeholders should be considered throughout development and implementation: automation of certain tasks using AI can impact professional autonomy and role identity (Berente *et al.*, 2021; Gronsund *et al.*, 2020; Mayer, Strich et Fiedler, 2020; Strich *et al.*, 2021), change workflow patterns (Sandhu *et al.*, 2020) or remove humans entirely from critical oversight roles (Rinta-Kahila *et al.*, 2022).

3.2.2 Characteristics of AI Systems

Previous research has noted that AI systems differ from other types of information systems in many ways, such that existing project management and system implementation frameworks may not be sufficient to support AI development and implementation. As noted above, these frameworks may not be suitable to analyze the outcomes of AI development and implementation (Vial *et al.*, 2023; Wrobel *et al.*, 2025). This mismatch can be attributed at least in part to the characteristics of current AI-based systems that use machine learning. Several characteristics of AI-based systems may impact users and organizations during development, deployment, adoption, and use, and therefore the extent to which existing research on general IS development and implementation applies to these systems is unknown.

First, AI systems, particularly those using machine learning algorithms, are often **inscrutable** (Berente *et al.*, 2021; Burrell, 2016; Schuetz *et al.*, 2020). There are four dimensions of inscrutability: auditability, explainability, transparency and interpretability. Auditability and explainability are properties of AI algorithms and directly apply to current ML techniques. <u>Auditability</u> refers to the fact that AI-based systems use complex approaches such as neural networks, where the logic of the system is not accessible to human developers (Burrell, 2016). While they may simulate human intelligence (Benbya, Davenport et Pachidi, 2020), AI-based systems are often considered black boxes (Berente et al., 2021) because their inner workings are opaque – even to those who develop them (Asatiani *et al.*, 2021; Marabelli *et al.*, 2021; Reis *et al.*, 2020; Zhang *et al.*, 2021). This is in contrast to traditional computer code, which can be inspected by programmers, facilitating changes and correction (Schmelzer et Walch, 2024). <u>Explainability</u> is closely related to opacity and refers to the fact that AI algorithms are often difficult or impossible to codify and to understand (Berente et al., 2021). <u>Transparency</u> on the other hand is a managerial issue and refers to the willingness of the AI-system developers to disclose certain elements of the algorithms (Berente et al., 2021). <u>Interpretability</u> is directly related to the human user, as it refers to the ability of the user to understand and make sense of the algorithm's output. As such, interpretability is not a direct property of the algorithm itself, but is dependent on the learning style, skills and abilities of the user (Berente et al., 2021). Inscrutability of AI systems can impact the trust of users and other stakeholders impacted by their use (Von Eschenbach, 2021).

Second, current AI systems are designed to learn and are therefore **dependent on data** for initial development and for ongoing application and improvement. These systems are designed to learn and discover patterns from large quantities of data (Burrell, 2016; Davenport *et al.*, 2025). The quantity and quality of the input data can directly influence the output of AI systems. It is imperative to clearly and carefully establish the initial "ground truth" on which these systems are trained. Beyond ensuring the quality of the input data, in some cases, establishing the ground truth involves codifying tacit knowledge (Gronsund *et al.*, 2020; Lebovitz *et al.*, 2021; Mayer, Kotlarsky et Oshri, 2024; van den Broek *et al.*, 2021). One impact of data dependency during operations is the tendency of ML algorithms to reproduce the biases found in their training data (Berente *et al.*, 2021; Davenport *et al.*, 2025).

Third, because they are designed to uncover patterns in data rather than follow deterministic code, and to learn from new data over time, AI-based systems are **unpredictable**. One implication of the learning nature of AI algorithms is that their output changes over time, either because of changes in the input data, or because of new relationships the system learns and applies. Changes in the source data between the time of system design and system implementation can influence the system output, sometimes in significant and unpredictable ways (Schuetz *et al.*, 2020). These changes could occur because live data behaves differently from archival data on which a system was initially trained, or because there are unanticipated changes in the source data over time (Ackerman *et al.*, 2021; Vial *et al.*, 2021). As a result, there may be mismatches between the original objectives of the system and its actual output which may only become apparent once the system is in use (van den Broek *et al.*, 2021). The unpredictable nature of the system output can impact end-users' ability to effectively use the system output (Sturm *et al.*, 2021), but also means that these systems must be constantly monitored to ensure they continue to meet their objectives.

Fourth, once deployed, many AI systems are often designed to **act autonomously**, replicating and replacing organizational operations and human decision-making, often without explicit human direction or oversight (Baird *et al.*, 2021; Berente *et al.*, 2021). Increasingly advanced AI systems can make decisions and act on their algorithmic predictions (Berente et al., 2021). The level of autonomy and responsibility given to these systems can impact workflows (Mayer *et al.*, 2020), human oversight capabilities (Rinta-Kahila *et al.*, 2022), and the mode of interaction between humans and machines (Berente et al., 2021). The reallocation of tasks from humans to AI algorithms requires human actors to adjust to a new workflow (Mayer et al., 2020). The autonomy of some AI systems, coupled with the increasing speed of data generation and incorporation of AI in organizations, limits human oversight capacity and capability (Berente et al. 2021, Rinta-Kahila et al., 2022). New configurations of workflows can also involve machines delegating to humans (Baird *et al.*, 2021; Schuetz *et al.*, 2020), such as in the case of algorithmic management (Jarrahi *et al.*, 2021).

While current research on AI-based systems demonstrates that they differ in significant ways from other types of IS, what is less understood is how these characteristics impact how organizations navigate the development and implementation of AI and effectively integrate these systems in a way that they can be used by many organizational actors. This meta-synthesis will examine cases of AI development and implementation, to understand how this process may work.

3.3 Method

A meta-synthesis of qualitative case studies is an approach that employs qualitative methods to synthesize qualitative data from published case studies (Habersang et Reihlen, 2024; Hoon, 2013; Skinner, Nelson et Chin, 2022). Meta-synthesis allows researchers to benefit from a broader potential scope of cases than when conducting primary data collection. In addition, combining individual qualitative studies increases their usefulness as this process helps to extend knowledge on a given phenomenon (Habersang *et al.*, 2024). It is a particularly appropriate method for synthesizing knowledge on complex interventions such as system implementations (Paré *et al.*, 2015). Furthermore, the method allows for the integration of multiple perspectives on the same topic, such as system users and department or organizational managers, and takes into consideration contextual factors, such as geographic or industry-related factors (Hoon, 2013). In IS, this approach has been used to understand the responses of implementers to IS resistance (Rivard *et al.*, 2012); how the emergence of project persistence contributes to project escalation (Berente *et al.*, 2022); and institutional responses to IS resistance (Berente *et al.*, 2019). This meta-synthesis of qualitative case studies followed the method proposed by Hoon (2013).

Meta-syntheses can provide different insights from other types of literature reviews. In recent years, several literature reviews have been published on the topic of AI implementation (e.g., (Enholm *et al.*, 2022; Lee *et al.*, 2023; Paleyes *et al.*, 2022). Paleyes et al. (2022) examine challenges in machine learning deployment through a survey of case studies, review papers and "lessons learned" practitioner reports. Their study focuses primarily on the technical aspects of the machine learning workflow, but does not cover organizational implications, nor does it empirically connect challenges with specific practices adopted to address them. Enholm et al. (2022) synthesize empirical and conceptual papers related to AI and business value. They offer a list of enabling factors and first- and second-order impacts of AI in organizations, but do not empirically connect the enabling factors and the impacts of AI. Lee et al. (2023) provide a list of antecedents to AI implementation, challenges of AI implementation, guidelines for AI implementation and consequences of AI implementation extracted from empirical and conceptual papers. Similar to Enholm et al. (2022), Lee et al. (2023) do not demonstrate the link between challenges, consequences and guidelines for AI implementation.

Meta-syntheses have several limitations. First, the researcher does not have access to the entire data set (interview transcripts, field notes or documentation for example), and thus the data is limited to what is published in the article and associated appendices (Hoon, 2013). This limitation can be addressed by only including cases that present sufficient detail of the phenomenon being studied and include excerpts of primary raw data (for example, quotations from interviews or excerpts of documents) (Hoon 2013). In addition, the authors of the primary case studies can be contacted to obtain additional information and details that were not in the published version. A second limitation is that the results of qualitative research are often influenced by the research methods and epistemological positions of the primary case authors (Zimmer, 2006). The research method adopted in the primary case studies may influence the results that are presented in each of the published cases. In this essay, for transparency, a coding form (see **Appendix F**) was used track the research method used and the epistemological position of the original authors.

3.3.1 Steps for meta-synthesis

This meta-synthesis of qualitative case studies followed the method presented in Hoon (2013). The seven steps are detailed below. Steps 1-3 involve identifying relevant literature to synthesize. Step 4 involves coding the data from the primary studies, step five involves analyzing this data, and steps 6 and 7 involve synthesizing this data. These steps are summarized below (see **Table 3-1**). It is important to note that these steps are described and presented sequentially for ease of comprehension, but that they were in fact conducted iteratively. In the sections below, each step is explained in greater detail.

Table 3-1 Steps in Meta-synthesis of Qualitative Case Studies (Adapted from Hoon 2013)

Step in meta-synthesis approach	**Analytical Goal**	**Strategy or procedure used**
1. Frame the research question	Develop a conceptual framing of the study and the phenomenon	Specification of the research question a priori
2. Locate relevant research	Identify a body of relevant case studies that describe and analyze the implementation and use of AI-based systems	Literature search (manual search in targeted journals, keyword search in databases, backward and forward search from relevant publications)
3. Determine and apply inclusion and exclusion criteria	Ensure that included studies are relevant based on method, topic, and quality	Clear inclusion and exclusion criteria and clear quality assessment strategy applied to retrieved research
4. Extract and code the data	Extract the insights from the study as well as any contextual information that may contribute to study outcomes	Data collection form used systematically collect and code data from each study
5. Case specific analysis	Obtain a rich, detailed understanding of each case	Within-case analysis, development of case-specific casual networks

6. Cross-case synthesis	Obtain an overarching understanding of the phenomenon	Cross-case comparison, pattern-seeking, merging data
7. Theory building from meta-synthesis	Development of theory (new theory or theoretical extension)	Link results to literature

3.3.2 Step 1: Frame the Research Question

Like many literature reviews, a meta-synthesis begins with the *initial conceptual framing* of the topic and the definition of the research question and definition of key concepts and constructs(Webster et Watson, 2002). The initial research question focused on the implementation process and post implementation period of AI systems; however, when reviewing the cases, we found that development and implementation of AI systems were often inextricably linked. The study was therefore reframed to focus on understanding how organizations navigate this entire period, and the research question was broadened and became *How do organizations navigate AI system implementation, from development through widespread organizational use (or abandonment)?*

3.3.3 Step 2: Locate Relevant Research

A comprehensive search strategy was used to obtain as many published cases of AI implementation as possible. The literature search combined a database search, a manual search of a selected set of publications and backward and forward search strategies (Hoon, 2013; Webster *et al.*, 2002). As per Webster and Watson (2002), the search began in high-quality journals with a manual search of all papers published in the Senior Scholars Basket of Eleven journals ("basket") between 2016 and 2023. Only publications from 2016 and later were considered, because this year marks the beginning of widespread commercial interest in AI-based systems.[11] This search sought to identify papers recounting case studies of implementation of an AI-based system, and to identify appropriate keywords for a subsequent database search. In addition to the "basket" journals, a manual search with the same objectives was also conducted in MISQ Executive, which regularly publishes rich case studies relevant to information systems research and practice.

[11] In early 2016, CIO magazine reported that AI was poised to become an important technology that year but did not cite examples of actual systems that had been implemented, only future projects that were planned for the year (https://www.cio.com/article/218240/the-reality-of-artificial-intelligence-in-2016.html). In late December 2016, The Guardian noted that 2016 was the year that AI "came of age," giving as examples that Google Home and Alexa voice assistant services became available and were deployed in millions of homes (https://www.theguardian.com/technology/2016/dec/28/2016-the-year-ai-came-of-age). In 2017, Ransbotham and colleagues noted that, while adoption was not yet widespread, 20% of firms were exploring with applications of AI, and 5% of them had adopted the technology extensively (Ransbotham et al., 2017).

Recognizing that studies of AI system implementation may be reported outside the IS field, and that reports of these cases can enrich our understanding of AI system implementation, an interdisciplinary database search was also conducted using the Web of Science, ABI/Informs, AIS Electronic Library databases in June 2023, and the ACM digital library and the IEEE Xplore Digital Library in April 2024. The search string included variants of the terms "artificial intelligence," "machine learning," "intelligent system," "cognitive agent," "learning algorithm," or "algorithmic decision-making," for the topic, and "case study" or "interview study" or "qualitative study" for the method. Boolean operators were used to develop the search string. Journal publications, conference proceedings and book chapters were searched for relevant cases. Filters were used to limit results to peer reviewed publications, in English, published in or after 2016. See **Figure 3-1**

The search returned several literature reviews about the implementation and use of AI in organizations (Coombs *et al.*, 2020; Enholm *et al.*, 2022; Lee *et al.*, 2023; Nguyen, Sidorova et Torres, 2022; Paleyes *et al.*, 2022). These literature reviews synthesized conceptual and empirical work and provided a list of factors that may affect development and implantation but did not focus on the processes of development and implementation and how the process might impact the outcome. Nonetheless, the bibliographies of these literature reviews were a useful source of potential studies. They were therefore searched, and any additional studies identified were included in the final sample of studies (Hoon, 2013). In addition, backward and forward searching of the studies retained for the review was conducted (Habersang *et al.*, 2024; Webster *et al.*, 2002). All studies retrieved by all search strategies were organized in a single database using the reference management software Endnote.

Search terms:

TOPIC:

Search terms were: "artificial intelligence" OR AI OR "machine learning" OR "intelligent systems" OR "cognitive agent" OR "learning algorithm" OR "algorithmic decision-making"

METHOD:

Search terms were: "case study" OR "case studies" OR "interview study" OR "qualitative study" OR "qualitative research"

Filters:

PUBLICATION TYPE:

Depending on database functionalities, search results were either a) refined using filters in the database to only include peer reviewed empirical publications; or b) refined manually to exclude publication types that were irrelevant, such as editorial material, literature reviews, conceptual papers or meeting abstracts.

PUBLICATION DATE:

Search results were restricted to publications after 2016

LANGUAGE:

Only English-language publications were included

Figure 3-1 Search Terms and Search Strategy

3.3.4 Step 3: Define and Apply Inclusion and Exclusion Criteria

Once potential literature has been identified, a critical step in any literature review is determining which studies to include. Rigorous and relevant inclusion and exclusion criteria that reflect the research question must be established and applied (Templier et Paré, 2015). For a study to be included in the review, it must correspond to the subject matter of the review and meet minimum quality standards. Included studies reported primary empirical data of the implementation (or attempted implementation) and use of an AI-based system in an organization. Studies that reported work in progress with limited empirical evidence were excluded, as were those that focused exclusively on the development of a system but not its implementation, only on system use but not its implementation, or only on a system that was never introduced to an organizational setting. Widespread use in practice is defined as long-term use of an information system that is fully embedded and used in an organization (Marabelli *et al.*, 2021). In this study, we were interested in understanding how implementation unfolds, from initial ideation through widespread use or abandonment. To be included in our sample, the paper needed to cover the implementation period but did not need to present all steps in the trajectory in detail. In this way, the meta-synthesis aims to provide an understanding of all phases of implementation and development.

For aggregative reviews such as meta-synthesis that aim to build theory, it is important to ensure that studies included in the review are of sufficiently high quality (Templier *et al.*, 2015). Studies that were not peer-reviewed, did not use a rigorous case study method (see (Dubé *et al.*, 2003; Yin, 2014) for criteria of rigor and validity in case study research) were excluded. Following Hoon (2013), studies that did not include excerpts of primary data (e.g. quotations) were also excluded. In addition, studies that report aggregated findings from multiple cases where the reader cannot clearly separate each of the individual cases were excluded. See **Figure 3-2** for an illustration of the literature search and **Table 3-2** for a description of included cases and corresponding studies. In total, 22 papers were identified, which together presented 12 distinct cases. Some cases were discussed in multiple studies, and one study presented multiple cases.

Table 3-2 Summary of Inclusion and Exclusion Criteria

Inclusion criteria	**Description/examples**
Empirical case study	- Single case study - Multi-case study
AI-based system	- System incorporates AI, including machine-learning
System implementation in an organization	- Study includes some details of the implementation of the system (can be a phased or iterative implementation process) but does not need to cover the entire development and implementation process in detail.
Peer-reviewed publication	- Journal paper - Book chapter - Conference paper published in proceedings
Exclusion criteria	**Description/examples**
Does not report primary empirical evidence	- Conceptual or theory paper - Literature review - Editorial material - Opinion piece - Research method paper
AI implementation is not a focus of the study	- Papers where AI or machine learning is used as the research method - Papers where the development and implementation of AI is not the focus (e.g. the term “artificial intelligence” is used as an example of recent technological innovations in the introduction or conclusion, but is not featured in the study)
Study not in an organizational context	- Study focuses on the development or implementation of a system not used in an organizational context (e.g. autonomous vehicles; smart homes)
Does not report on the implementation of the AI system and its impact on users or the organization	- Papers that only report on the design or development phase but not the implementation - Papers that only report on the outcomes of a system but do not provide details of the implementation process
Low quality	- Research method not described: data collection or analysis not rigorous or well documented - Paper does not present any raw empirical data
Limited usability of data*	- Paper presents aggregated findings from a multiple case study and the report of the findings does not enable the reader to clearly distinguish findings from each individual case. - Research-in-progress where only preliminary evidence is presented and where no complete version of the study is available.

*The corresponding author of papers that exhibited limited usability was contacted and asked to provide additional information on these cases, published or not. No additional information was available.

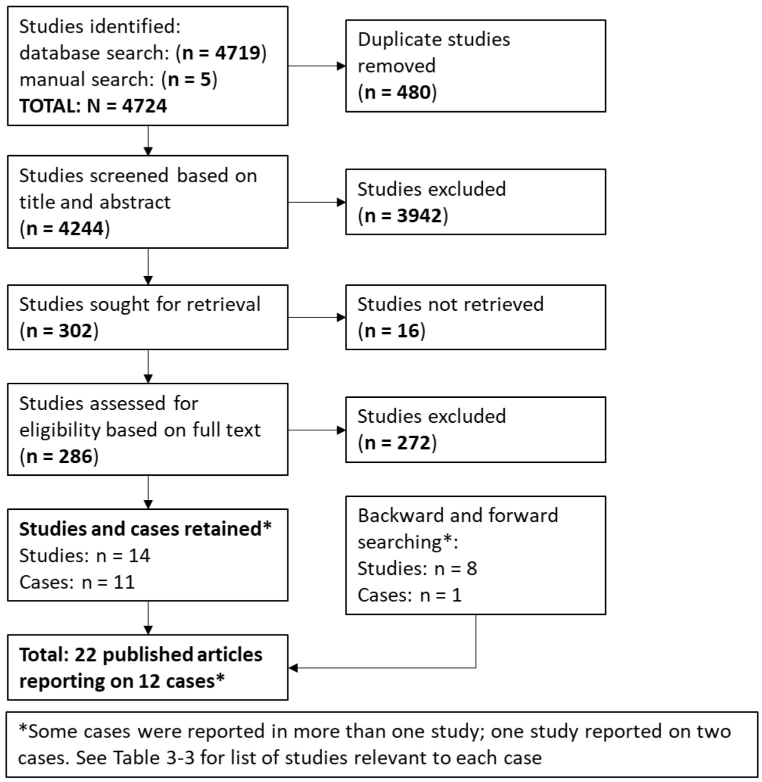

Figure 3-2 Flow Diagram of Literature Search

3.3.5 Step 4: Extract and Code the Data

The primary data for a meta-synthesis comes from published case studies. Therefore, once the sample of cases to be included has been identified, the researcher must systematically extract the data from these primary cases. The full text of each study deemed relevant for inclusion is read and coded in preparation for analysis. When a study reported on more than one case, a separate form was completed for each case.

A coding form was developed to systematize the coding process (Hoon, 2013). The initial coding form (see **Appendix F**) was deliberately extensive but allowed for new codes to be added as coding progressed. First, coding for a wide variety of information helps ensure that relevant information is recorded. Second, the information extracted can be useful for detailed quality assessment. Finally, as it may not be known a priori which contextual information from the primary studies may be relevant, deliberately extracting a high level of detail allows for the comparison of a variety of potential contextual factors. Some sections of the coding form help to extract and organize the data, others help evaluate the quality of the studies included, and still others serve statistical/measurement purposes. The nature of the information entered into the coding form varies depending on the information being coded. Some fields in the coding form are pre-determined, some are categorical, and some are open-ended.

The coding form included an initial set of codes such as contextual information about the study and details of the system being implemented. It also included codes derived from theoretical constructs from IS development and implementation, and the four characteristics of AI[12]. Coding proceeded iteratively, moving between the papers and the coding form. Information about each case that did not fit the previously defined coding scheme but appeared relevant to the research question was also captured and coded. When new codes appeared in more than one case, the coding form was modified, and all cases were recoded for these additional codes. One technique to favour reliability of coding, to reduce mistakes and to avoid omitting relevant information is to employ multiple coders (Miles *et al.*, 2013). The first author coded all studies. To assess coding reliability, the coding scheme was shared with the second author who reviewed the coding for a subset of cases. An initial agreement of over 75% was reached between coders, and discrepancies were resolved through discussion (Berente *et al.*, 2019). Throughout coding, codes were validated across cases to ensure consistency of meaning and interpretation (Noblit et Hare, 1988).

3.3.6 Step 5: Case Specific Analysis

Similar to multiple case studies that use primary data, the cases included in a meta-synthesis are first analyzed individually (case-specific analysis) and then synthesized (cross-case synthesis). Case specific analysis sought to describe and explain what happened in each specific, bounded context, allowing the researchers to familiarize themselves with the data of each case and generate preliminary theory based on the patterns that emerge from each case (Eisenhardt, 1989; Miles *et al.*, 2013). It involved writing brief narratives of each case using the information extracted in the coding forms; indicating what happened in each of the phases or cycles of development and implementation in each of the cases; and determining how the elements in each case influence its outcomes (Hoon, 2013; Miles *et al.*, 2013). In addition, causal networks were developed for each case individually. The goal of the case-specific causal networks was to help

[12] To assess the extent of inscrutability, each of the four dimensions of inscrutability were assessed separately. To render the directionality of the assessment of each dimension parallel, in the coding form, "opacity" is referred to using its opposite, "auditability."

understand how each case unfolded, the outcomes and impact on all stakeholders discussed in each of the cases, and what factors contributed to the outcomes in each of the cases, not to produce definitive causal diagrams. This step was highly iterative and involved moving back and forth between coding the studies, creating causal networks, refining the coding form and revising the codes.

3.3.7 Step 6: Cross-Case Synthesis

Once each case had been analyzed on its own, cross-case synthesis was conducted to find patterns or similarities among the cases (Miles *et al.*, 2013). Thorough, structured searching across cases enhances the likelihood that the researcher can identify novel insights and patterns (Eisenhardt, 1989). Several different techniques can be used to represent the cross-case synthesis. In this study, comparative tables were developed to highlight similarities and differences between cases (Miles *et al.*, 2013; Noblit *et al.*, 1988).

Cross-case synthesis can have many different objectives. The objective of the synthesis depends on the research question of the study, and on the insights from the data. Cross-case synthesis can be conducted to highlight patterns among cases or identify themes across cases (Braun et Clarke, 2006). It can be used to develop meta-causal networks or other generalizations and enhance transferability of the results to other contexts (Miles *et al.*, 2013). It can also be used for grouping cases into categories that are organized according to certain dimensions. One example is set-theoretic approaches (Charles C Ragin, 1987). These approaches assume equifinality, i.e., that there are multiple paths to a given outcome, and so grouping cases based on sets of dimensions is appropriate. Another approach is to synthesize the data in tables or matrices which highlight key constructs or variables (Eisenhardt, 1989). Visual representations of causal and meta-causal networks can be developed to represent the emerging insights of relationships between constructs (Miles *et al.*, 2013). In either situation, it is important to always refer to the original case studies to ensure that the synthesized representation accurately represents the original findings. Finally, it is important to note that a meta-synthesis approach is designed to synthesize findings of multiple cases, even if the assumptions, methods and types of participants are different in each of the original cases (Miles *et al.*, 2013).

In this study, we began by creating meta-causal networks but found that the heterogeneity among the data available and the contexts of each of the cases limited the effectiveness of this approach. Similarly, there was limited data reported on the long-term outcome each case to effectively compare the cases using a set-theoretic approach, as these approaches require a clear understanding of outcomes to be able to compare pathways leading to different outcomes. For these reasons, we opted to produce summary tables that synthesized the findings, presenting areas of overlap and highlighting areas where the cases differed.

3.3.8 Step 7: Theory-Building

The goal of a meta-synthesis is to make a theoretical contribution (Hoon, 2013). In this study, the evidence in each case was first used to sharpen the definitions of the constructs (Eisenhardt, 1989). Some of the phases of development required sharper definitions, such as dataset curation and workflow redesign. Other constructs that appeared relevant in the development and implementation of AI systems that needed to be properly defined were cultivation of in-house expertise, openness to compromise and transcending explainability.

Next, emerging relationships among the constructs were identified in a first step to move from constructs to a theory (Miles *et al.*, 2013). The analysis identified relationships between characteristics of AI, their impact on the development and implementation of AI systems, and specific tactics used to address the impact of the characteristics of AI. The authors re-examined all cases to see if the relationships fit, or if there was evidence of misfit. While the analysis of the cases could not confirm causal relationships between the impact of characteristics and specific mitigation tactics, several impacts of AI characteristics appeared correlated with mitigation tactics. Similar to multi-case studies using primary data, throughout the theory-building process, emerging theoretical insights were constantly compared with the data from the published cases and extant literature (Eisenhardt, 1989).

3.4 Findings and Analysis

3.4.1 Within case analysis

In the following section, we present a descriptive summary and within-case analysis of the cases included in this meta-synthesis. Twelve cases of AI system development and implementation were identified through the literature search. The analysis in this meta-synthesis is based on the data available in the published cases. For many of the cases included in this study, it is possible (and likely) that implementation continued beyond what is reported in the case, but the findings reported in this study are based on the information available in the publications. The context, type of system, goal and outcomes of implementation of each system are summarized in **Table 3-3** and **Table 3-4**.

3.4.1.1 Context and purpose of the AI systems included in meta-synthesis

The cases were implemented in industries including public services, academia, health care, private enterprise, and logistics, and took place in Europe, the US and Australia. The systems featured in these cases all used machine learning techniques. The goal of the systems in these cases included improvement of *operations* (cases 1, 3-9 and 11-12), *services* (cases 2-3), *patient care* (cases 6, 8 and 9) or *organizational finances* (cases 10 and 11)[13]. Many of the systems were implemented to leverage the analytical capabilities of AI to analyze large amounts of data to improve the quality of decisions. The Anamnesis tool in Case 9 additionally aimed to improve documentation of patient care. In contrast, IBM's Watson was implemented at Deakin (case 3) to provide an additional channel of communication for students. Cases 1 and 4-12 featured custom-made systems developed for the client mentioned in the case. Case 2 featured a system developed for implementation in several states in the United States criminal justice system, and case 3 described the implementation of IBM's Watson in a university.

3.4.1.2 Outcome of system implementation

To determine if certain factors or combinations of factors led to certain outcomes of system implementation, we also examined the outcome of system implementation in each case. Two systems were abandoned and therefore considered *failures*: case 9, a cognitive agent designed for use in a hospital, did not progress past an initial introduction to users due to resistance by physicians; and case 10, an algorithmic system that calculated welfare overpayments and automatically notified recipients, was deployed and used but ultimately withdrawn after public outcry determined it was damaging. Eight systems (cases 2, 3-8 and 11-12) were *used as intended*, as they were deployed and used as intended by users in the organizations where they were implemented. The system in the remaining case was implemented and used, but not as intended, and therefore the outcome is considered *mixed*. In case 1 (a system designed to predict locations of criminal activity), following implementation, users developed a simpler parallel system and only used the AI system to confirm their analysis from this parallel system.

3.4.1.3 Evidence of characteristics of AI in cases

The cases were also analyzed to determine to what extent they exhibited the characteristics of AI. All cases exhibited at least one characteristic, with most exhibiting many, but few exhibited all four to a great extent. See **Table H-1 in Appendix H** for detailed coding of the presence and impact of the characteristics of AI in each case. **Inscrutability** depends on four dimensions: opacity and explainability of the algorithm, interpretability of the output, and

[13] Some systems had multiple objectives, which is why they are listed more than once.

transparency of the developers (Berente et al., 2021). In this study, assessing the inscrutability of the systems involved aggregating an assessment of all four dimensions. The level of overall inscrutability exhibited in the cases varied, ranging from low (case 4, ShipCo and case 7, Low Bed Tool) to high (case 1, CAS), with most cases in the middle. Because explainability refers to being able to understand how and why an algorithm makes certain predictions, and opacity refers to the ability to audit the inner workings of an algorithmic model, they do not always vary in parallel. Such was the case in cases 4 (NeuroYou) and 11 (CleverLoan), which both featured explainable algorithms that were also opaque. This demonstrates that the explainability of an algorithm alone is not a sufficient measure of the extent of inscrutability of an AI system. A lack of transparency on the part of the developers can significantly impact overall inscrutability, even when the system is explainable and not opaque, and when the output can be easily interpreted. This was the case for Robodebt (case 10): the system was explainable and not opaque, and the output was easily interpretable, but the details of how the algorithm was designed and what data was incorporated were not made available.

Current AI systems are designed to learn from data and operate using real time data, meaning that their output may be unpredictable, and may change over time. All systems were dependent on high-quality **data** both for training and operation. The definition of quality depended on the case, but all cases required specific, accurate, and local data for training. Most cases required consistent access to real-time local data for operation (the exception being case 3, Watson, which needed the source data to remain up to date, but not a steady stream of new data).

The **learning-driven unpredictability** of the system output was not present in all cases. Often, unexpected results would be generated during development of the system, triggering modification of the algorithm, such as in cases 5 (ShipCo), 6 (Readmission Risk tool) and 7 (Low Bed Tool). In other cases, the system would sometimes generate surprising results, such as predicting car theft in a no-parking zone (case 1, CAS), predicting sepsis in a patient the physician did not expect (case 8, Sepsis Watch) or providing different loan recommendations for seemingly similar applicants (case 11, CleverLoan). In NeuroYou (case 4), the system appeared to frequently generate recommendations completely contrary to hiring managers' expectations. In the Robodebt case, the system frequently miscalculated debts owing, but this was attributed to the dataset, not the underlying characteristics of the AI system.

Finally, the systems in this study exhibited varying degrees of **autonomy**. Six systems made predictions, but humans had full autonomy to accept or reject these predictions (case 1, CAS; case 2, COMPAS; case 6, Readmission Risk Tool; case 7, Low Bed Tool; case 8, Sepsis Watch; and case 12, Rayfood). In cases 2, 6 and 7, users reported relying extensively on the AI system's predictions when making decisions. In case 8, the Sepsis Watch nurse would contextualize the system's recommendation before sharing it with the attending physician, and the physician would validate the recommendation before acting on it. In cases 4 (NeuroYou), the system was designed to autonomously create a shortlist of candidates, necessarily eliminating the majority. While users could make a final selection based on the shortlist, they were not able to go back to the original list of candidates. In case 5, the system was designed to ultimately replace the researcher, autonomously generating trade tables. However, the brokers were not required to use the system output when making final recommendations. Four systems were designed to be fully autonomous and operate without oversight or override capability: Watson (case 3) independently replied to student queries; the Anamnesis system (case 9) was designed to autonomously conduct and document patient intake and subsequently update the patient's EHR; Robodebt (case 10) autonomously calculated debt overpayment and issued repayment notices; and CleverLoan (case 11) automatically determined loan eligibility and made an irrevocable decision.

3.4.1.4 Consequences attributed to characteristics of AI

The consequences attributed to these AI characteristics were also captured (see final column of **Table G-1** in **Appendix G**). In three cases in this study, these impacted the system implementation in a way that had overall negative consequences for the organization that were insurmountable. In case 9 (Anamnesis), physicians perceived system autonomy as a potential risk to liability. In addition, they were unwilling and unable to provide the detailed data on physician-patient interactions required to improve the system. Implementation of this system was postponed indefinitely. In case 10 (Robodebt), limitations in data quality coupled with lack of oversight of an autonomous system resulted in damages to both civilians and the reputation of the government service, and ultimately leading to system abandonment. In case 1 (CAS), the inability to overcome high inscrutability and learning-induced unpredictability led the intelligence officers to engage in workarounds, not using the system as intended. In addition, three cases mentioned that overreliance on AI-generated recommendations may lead to erosion of critical thinking ability and organizational knowledge (cases 8, Sepsis Watch; 9, Anamnesis; and 11, CleverLoan). These negative consequences were not observed and reported in the cases, likely because the systems had not been in place for long enough at the time of publication.

Not all negative consequences were insurmountable. In most cases, data dependency prompted careful curation of the dataset used by the system (see below, **section 3.5.2**). In case 4

(NeuroYou), although the system itself was opaque, the developer's transparency regarding input data and parameters ensured Multico knew what was being measured, and efforts to increase interpretability contributed to the usability of the system output. In case 5 (ShipCo), the researcher expressed concern that the system would replace her. She was reassured by the CIO that her role would simply change. This role change was not reported in the case, however. In case 8 (Sepsis Watch), the physicians reported low trust in the system during the early days following implementation, but this appears to have been resolved over time as they were able to observe the accuracy of the system output and the positive performance impacts.

Table 3-3 List of Cases Included in Meta-Synthesis and Sources

Case	**Industry**	**Purpose of system**	**Location**	**References**
1. Crime anticipation system (CAS)	Policing	Inform allocation of police resources	Netherlands	(Waardenburg, Sergeeva et Huysman, 2018; Waardenburg, Huysman et Agterberg, 2021; Waardenburg, Huysman et Sergeeva, 2022);
2. COMPAS	Criminal justice system	Determine risk of reoffence	US	(Haeri *et al.*, 2022; Hartmann et Wenzelburger, 2021)
3. Watson	Higher education (University)	Answer student questions	Australia	(Scheepers *et al.*, 2018)
4. NeuroYou	Hiring	Conduct initial screening of candidates	Europe	(van den Broek *et al.*, 2021; Waardenburg *et al.*, 2021)
5. ShipCo	International shipping	Provide analytics to support shipping brokerage	Europe	(Gronsund *et al.*, 2020)
6. Readmission risk tool	Health care (Hospital)	Predict risk of readmission	US	(Singer *et al.*, 2022)
7. Low Bed tool	Health care (Hospital)	Predict clinic capacity	US	(Singer *et al.*, 2022)
8. Sepsis Watch	Health care (Hospital)	Predict risk of sepsis	US	(Bedoya *et al.*, 2020; Sandhu *et al.*, 2020; Sendak, Elish, *et al.*, 2020; Sendak, Ratliff, *et al.*, 2020)
9. Anamnesis tool	Health care (Hospital)	Facilitate patient intake	Germany	(Reis *et al.*, 2020)
10. Robodebt	Public services	Automate calculation and reclamation of welfare overpayments	Australia	(Mead et Barbosa Neves, 2023; Park et Humphry, 2019; Rinta-Kahila *et al.*, 2022)
11. CleverLoan	Banking	Automate small loan decisions	Germany	(Mayer *et al.*, 2024; Mayer *et al.*, 2020; Strich *et al.*, 2021)
12. Rayfood	Food services	Automate extraction of nutritional information	US	(Stéphanie Camarena, 2022)

Table 3-4 Summary of Systems in Each Case

Case	Data sources	AI/ Algorithmic Approach used	Goal of implementation	Users	Outcomes
1. CAS* **	Source: Historical police data from across the country. Nature: Data on high-impact crimes with high reporting numbers.	Logistic regression analysis learning algorithm	Identify areas with a high likelihood of crime to facilitate police officer resource allocation.	System users were intelligence officers; system output users were police managers.	**Mixed**: System implemented but ultimately not used as intended: intelligence officers developed workarounds.
2. COMPAS*	Source: Historical data from criminal justice system. Nature: Conviction and re-offense history.	Classification algorithm	Improve risk assessment and delivery of criminal justice programs.	System and system output users were actors in criminal justice system.	**Success**: System implemented and used. Criminal justice actors appreciated the reduction in uncertainty.
3. Watson*	Source: knowledge base provided by students and staff. Nature: unstructured text.	Rule-based NLP cognitive agent	Improve student experience, in line with general digital transformation efforts.	System users were primarily students, but also university staff.	**Success**: System implemented and used. Information on impact not available.
4. NeuroYou**	Source: generated from NeuroYou's online games Nature: personality and skills	Machine learning algorithm	Speed up hiring and identify better candidates.	System users were candidates; system output users were hiring managers.	**Success**: System implemented and used. Hybrid hiring practice emerged.
5. ShipCo***	Source: AIS feed (subscription) Nature: raw data about ships and their movement	Classification algorithm using rule-based NLP classification	Speed up analysis process and take advantage of increased data in analysis.	System and system output users were analysts.	**Success**: System used by one segment, similar system in development for a second segment.
6. Readmission risk tool***	Source: Inpatient data Nature: structured and unstructured data	Random forest algorithm	Identify patients at highest risk of readmission to plan for care.	System and system output users were care managers.	**Success**: System used by intended users; increased efficiency and accuracy in readmission risk prediction.
7. Low Bed tool***	Source: Hospital census data Nature: Hospital bed occupation	Machine learning algorithm	Identify 3-5 days in advance when additional capacity was	System and system output user was	**Success**: System used by intended user;

	and duration of stay		needed in four hospital departments.	clinical manager.	improvements in operations.
8. Sepsis Watch* **	Source: Patient data stored in the EHR system Nature: medical history, vital signs, lab measurements	Recurrent neural network (RNN) coupled with a multi-task gaussian process (machine learning)	Early identification of patients at risk for sepsis so tests and treatment can be ordered.	System users were rapid response nurses; system output users were ED clinicians.	**Success**: System implemented and in use; changes in workflows and roles. Information on impact is not available.
9. Anamnesis tool* **	Source: Patient data stored in the EHR system Nature: demographic and health information	Cognitive agent including speech recognition; rule-based algorithms and NLP; RPA (to update patient records); neural network machine learning (to recommend treatment protocols)	Free up physician time spent on documentation, improve documentation.	System users were patients; system output users were physicians.	**Failure**: System demonstrated to users; physicians resisted the system; implementation postponed indefinitely.
10. Robodebt* **	Source: Two government systems (social security and tax office) Nature: aggregated data on income (fortnightly from social security, annually from tax office)	Automated data-matching system	Speed up and increase collection of welfare overpayments.	System users were public servants (who had limited oversight capability), system output impacted citizens.	**Failure**: System initially implemented and used, negative impact on population, system ultimately abandoned after public outcry.
11. CleverLoan** [14]	Source: internal customer data and external credit history (SCHUFA) Nature: dynamic and static customer data	Classification algorithm	Increase profitability of small loan segment, address personnel mismatch.	System and system output users were loan consultants.	**Success**: System implemented and used; increased profitability; changes in loan consultant role identity.
12. Rayfood**	Source: nutrition information	Optical character recognition,	Improve data quality and speed of data	System and system output users were	**Success**: System piloted in several school districts.

[14] Note: the system in case 11 was used as intended, but experienced loan consultants expressed concern about anticipated negative consequences of the system. In this study, case 11 is considered a success from the organization's perspective, because it was used as intended and it had a positive impact on organizational performance, but the negative consequences expressed by experienced loan consultants indicate that certain risks posed by the system may have been overlooked. This nuance is highlighted in the discussion.

	sheets provided by suppliers Nature: nutritional information and icons/logos	image recognition and classification algorithm	extraction, reduce food waste.	school food program administrators.	Information on impact not available.

*These tools were developed by external providers using proprietary, black-box algorithms. They were designed as generic tools that could be adapted to the specifics of multiple organizations.

**These tools were developed by external providers using proprietary, black-box algorithms. They were designed and developed specifically for the client mentioned in the case, with the possibility of being adopted by other organizations subsequently, pending contextual adaptations.

***These tools were developed either internally or externally, but specifically for the organization featured in the study, with no reported intent at the time of development to use them in other organizations.

3.4.2 Cross-case analysis

Below, we present the cross-case analysis from our meta-synthesis of how organizations manage AI development and implementation. Approaches used during development and implementation include using a phased and iterative approach to development and implementation; involving a multi-disciplinary development team that includes technical and non-technical team members; and carefully curating the dataset used to train and operate the AI system. Approaches used during development included frequent interactions with users; developers demonstrating openness to integrating user- and domain-driven change; and integrating knowledge from subject matter experts. Approaches used to manage the implementation of the AI system included encouraging AI and data literacy of non-technical employees; redesigning workflows; integrating knowledge brokers; at times, black-boxing the technology; and mandating or strongly encouraging AI system use. In the sections below, we present how each of these approaches were used in the cases in this meta-synthesis.

3.4.2.1 Approaches used during development and implementation

3.4.2.1.1 Conducting AI development and implementation in phases

An early step in the analysis of the cases involved identifying distinct phases or steps in the development and implementation of each of the systems. These phases were identified and coded abductively. Previous literature (e.g., Vial *et al.,* 2023) was used to generate a preliminary list of the phases of development and implementation of IS projects. Additional phases or sub-phases were coded based on evidence from the cases. In all, 10 distinct phases or steps were identified from the cases in the meta-synthesis. (see **Table 3-5**). While the phases are presented here in an order, development and implementation did not follow the same linear pattern across the cases in our sample, and not all cases described each phase. In all cases in this study, development and implementation followed a hybrid phased-iterative approach, echoing previous research on development of AI and ML (e.g. Vial *et al.,* 2023). Iteration between phases appeared to be just as important as the phases themselves.

Ideation refers to the strategic decision of why and how to use ML in the organization. It is during this phase that leadership (of the organization, or the division where the ML system is being implemented) analyzes organizational needs and determines if an ML-based system would be an appropriate solution for the issue they are facing. It is often at this time that the organization determines if development and implementation will be outsourced or internal, and whether an off-the-shelf or bespoke system is most appropriate. The *feasibility assessment* includes an assessment of fit between available ML methods, approaches and technologies, available and accessible data and organizational objectives for ML, as well as potential integration with organizational systems and processes. In previous literature, this has been referred to as a blueprint phase (e.g. Vial et al., 2023). *Dataset curation* involves extracting data and preparing it to train the algorithm. Because ML systems require data for training but also for ongoing use, this phase was essential for all cases. Dataset curation began early in development but often continued after an initial proof of concept was tested (e.g., cases 3-5 and 11). The development and training of an initial version of the proposed system using historical data is referred to as a *Proof of concept (PoC)*. In the case of an off-the-shelf system (e.g., cases 2 and 3) this phase involves training the existing system on local historical data. Following the proof of concept, a *minimum viable product (MVP)* involves development and testing of a version using live data, testing connections with live feed of data. During *user testing* the system is shared with a limited group of users who interact with it and provide feedback. When an ML system is deployed, it often provides new insights that can change the decision-making process in an organization, prompting a *workflow redesign*. The system output influences the work of system users, but also those whose work changes because of the system output, often requiring redesign of workflow where the system is implemented. *User training* involves explaining and demonstrating how the system works to all potential users within the organization. *Large scale deployment* refers to when the system is deployed to the entire organization or targeted department, and *widespread use* refers to when the system is used by all intended users.

3.4.2.1.2 Using multi-disciplinary teams

AI systems are often introduced to rapidly process large amounts of data to support human decision-making. However, the output of these decisions can impact people other than the system user. If unaddressed, the inscrutability and learning-driven unpredictability of AI systems can exacerbate negative impacts and limit system acceptability. This meta-synthesis highlighted that development teams for AI systems were multidisciplinary and involved many more people than those responsible for building a model and ensuring its successful implementation. Not all teams had the same composition, but in all cases individuals other than developers and data scientists were involved in development and implementation. In the cases in this meta-synthesis, implementation failed when there was limited participation of end-users in the development of the system (Anamnesis, case 9) or when SMEs were deliberately excluded from system development and not consulted prior to or during implementation (Robodebt, case 10). Below we explain the different roles played in the development and implementation of AI systems. Two roles appeared particularly important to addressing the characteristics of AI: subject matter experts during development and knowledge brokers during implementation.

Top leadership: In the cases in our sample, the top leadership of the organization was almost always involved at some point. This is likely because all these cases reported on the first major ML implementation in the featured organization. In most cases, top leadership was only involved during the ideation phase. ShipCo (case 5) and CleverLoan (case 11) were two exceptions, where top management was involved at key points throughout system implementation. At ShipCo (case 5), AI was introduced to redefine organizational operations. As such, top leadership – primarily the Chief Data Officer (CDO) – was involved at many points during system development and implementation, establishing and communicating the vision for the project, working directly with the data scientist to adjust the algorithm, and managing change by reassuring the researcher that the algorithm would not put her out of a job. At Main Finance, ML (CleverLoan, case 11) was introduced to redefine operations of the small loans department by handing over the entire small loan business to the AI provider. In that company, top leadership was involved in meetings and conversations with the developers throughout development and implementation.

Management: In this study, we define management as mid-level leadership within the organization, with responsibilities for managing either people or other resources. In the cases in our sample, management was involved in several phases. The roles of management included overseeing the development of the project and managing changes in responsibilities and in staff workflow following system implementation. For example, at Main Finance (CleverLoan, case 11) and MultiCo (NeuroYou, case 4), managers acted as an interface between the developers and the users, either by ensuring that the users' needs were considered in the ML system, or by ensuring the data required by the developers was being generated or collected by the users. In the NeuroYou project (case 4), HR managers at MultiCo reviewed the output of early iterations of the system. When the output was misaligned with the expectations of their team, they asked the NeuroYou developers to include certain parameters in the ML model, even if, according to the data scientists, these parameters didn't have predictive power. At Main Finance, as the CleverLoan (case 11) system evolved, the data scientists required additional data. The managers transmitted this request to the loan consultants and configured their workflow to ensure this data would be collected. In the case of the Low Bed Tool (case 7), hospital clinical administrators were involved in ensuring that the systems met the needs of the hospital and of the teams the system was being implemented for. They were consulted during early iterations of the system and were invited to make recommendations that were integrated into further iterations.

Technical development team (external or internal): In many cases in our sample, the AI system was developed by external consultants; In other cases, the system was developed internally by the organization's IT department or innovation team. In all configurations, the development team included technical specialists with the required expertise to manage large quantities of data and develop ML algorithms, such as data scientists and software developers or engineers. In case 8 (Sepsis Watch), physicians with data science expertise were also involved in the development of the system. The technical development team was responsible for preparing the data to be used in the ML system, building the model, conducting tests and sharing test results with users or managers.

Users: Users of the ML system were involved in different phases of development and implementation. There were two types of users identified in our sample of cases. Some users used the system themselves, using the output to improve their decisions. This was the case for the loan consultants at Main Finance (CleverLoan, case 11), the HR professionals at MultioCo (NeuroYou, Case 4), the Population Health Care managers in the Readmission Risk Tool case and the clinical administrators in the case of the Low Bed Tool. In other cases, one group of users would interact directly with the system, but another group of users would act on the system output. The CAS case provides an illustration: the intelligence officers (system users) used the ML system to produce reports that police managers (output users) would use to allocate police resources. Similarly, the rapid response nurses (system users) would use the Sepsis Watch system (case 8) to identify high-risk patients, but the ED physicians (output users) would order tests and determine patient care.

Other roles: Two roles emerged from the analysis as appearing useful for addressing inscrutability, learning-driven data dependency, and learning-driven unpredictability: Subject Matter Experts (SMEs) and Knowledge Brokers. The phases of development, and which stakeholders participated in which phase, are summarized in **Table 3-5** below.

Table 3-5 Phases of development and implementation and stakeholder participation

Case	**Ideation**	**Feasibility assessment**	**Dataset curation**	**PoC (historical data)**	**Ltd. deployment w/live data (MVP)**	**User testing**	**Workflow redesign**	**Broad user training**	**Large-scale Deployment**	**Widespread use**
1. CAS	Top		Dev	Dev	Top, Dev, User		User, KB		Dev, User, KB	User, KB
2. COMPAS	Top, Exp, SME		Mgmt, Dev		User, Exp		User, Exp	Top, Mmgt, User	User	User
3. Watson	Top	Top	Mgmt, User, SME	Dev	Dev, Mgmt, User	Dev, User		Dev, User, SME	Dev, Mgmt, User, SME	User, SME
4. NeuroYou	Top, Dev, SME	Dev	Dev, SME	Dev, SME.	Dev, SME		Dev, SME	Dev, Mgmt,	Dev, User, Mgmt,	User, Mgmt
5. ShipCo	Top, User		Dev, SME	Dev, User	Top, Dev, User, SME	Dev, User, SME	Dev, Mgmt		Dev, User	User
6. Readmission Risk tool	Top, Dev, User			Dev, User, Exp	Dev, User	Dev, User	User		Dev, User	User
7. Low Bed tool	Top, Dev	Dev, User	Dev, User	Dev, User	Dev, User	Dev, User		Dev, User	Dev, User	User
8. Sepsis Watch	Top, Dev, User, SME	Dev, SME	Dev, SME	Dev, User, SME	Dev, SME,	Dev, User	Dev, User, SME, KB	Dev, User, SME, KB	Dev, User, SME, KB	Dev, User, KB
9. Anamnesis	Top, User	Top, Dev		Dev, Top	Dev, User	Dev, User				
10. Robodebt	Top						Top	User	Dev	User
11. CleverLoan	Top, Dev	Top, Dev	Dev	Top, Dev, User	Top, Dev, User	Dev, User	Dev, Mgmt		Dev, User, Top	User

12. Rayfood	Top, Dev	Top, Dev	Dev	Dev	Dev, User				User	User
Legend: Top = Top leadership; Mgmt = Management; Dev = Developers (incl. data scientists); User = System users and system output users; SME = subject matter experts; Exp. = External expert, Gov. = Governance committee Blank = not reported in available data; Grey = evidence of this phase was limited; Black = publications indicate this phase did not occur										

3.4.2.1.3 Curating the dataset to support data quality

Because AI systems rely on and learn from data in training and during operations, ensuring the data used to train and operate the AI system if of the highest quality helps organizations gain value from AI systems. Dataset curation can be defined as an ongoing activity during AI system development and implementation that involves obtaining consistent access to relevant data, cleaning and preparing data for use in the AI model, and ensuring the data remains relevant throughout the AI system's life cycle. Some form of dataset curation was reported in all cases in our sample, but case 10 (Robodebt) (see **Table I-1 in Appendix I**). In case 1 (CAS), the training dataset was built using historic high-impact crime data from the Netherlands to maximize contextual relevance. The COMPAS system implemented in case 2 was developed using data from an urban area in California but was implemented in a rural county in Wisconsin. Therefore, it needed to be fine-tuned on local data to ensure its contextual relevance. An early step in implementing Watson (case 3) was developing the dataset, which involved collecting common questions and their answers. Dataset curation in case 4 (NeuroYou) continued throughout development, as additional datapoints were required to improve the performance and relevance of the system. Dataset curation efforts in case 5 (ShipCo) centred around ensuring data quality by subscribing to a higher-grained AIS feed and cleansing data to remove ambiguities. For the Readmission Risk Tool (case 6) to provide relevant predictions, information about patients stored in free-text format in the patient's EHR needed to be integrated into the system. In case 7 (Low Bed Tool), data quality issues stemmed from differences in the way data was collected among different departments, requiring harmonization. For Sepsis Watch (case 8) to be relevant to the local context, local patient data was collected and used to train the model. The data for initial training of CleverLoan (case 11) included historical client data from Main Finance and externally sourced credit ratings. In case 12 (Rayfood), the developers spent considerable effort to ensure comprehension of data. In addition, the providers of the data for the system were asked to modify their documentation to make it more usable by the Rayfood system.

Dataset curation often continued after an initial proof of concept was tested. For example, at Deakin (case 3), the content managers were responsible for maintaining content long after launching the system to ensure the system continued to be able to provide accurate responses. At

MultiCo (case 4), HR managers ensured that data being collected and processed by the ML system respected ethical and legal requirements and reflected hiring practices. In case 11 (CleverLoan), additional datapoints were added to the system as time went on.

Not all cases had evidence of sufficient dataset curation, or evidence of dataset curation at all. Both cases where dataset curation was insufficient or inexistent failed. In case 9, dataset curation was not sufficient. One barrier to successful implementation was the inability to collect and digitize data determined necessary for the system to work properly. While historical data was collected from patient health records, detailed documentation from patient-physician interactions could not be obtained, limiting the ability of the system to accomplish its objectives. In case 10, dataset curation appears not to have been taken seriously: underlying mismatches in the format of data from two different sources caused the system to make miscalculations, resulting in underperformance of the system and ultimately system abandonment. **Table I-1** provides evidence from the cases.

3.4.2.2 Approaches used during development

Three related approaches were used in the cases to manage the development of AI systems. In many cases, developers engaged in frequent interactions with users (including demonstrations). These interactions were often beneficial when developers were open to integrating user- or domain-driven changes to the system. To understand which system changes would have the greatest impact, in many cases, knowledge from subject matter experts was solicited.

3.4.2.2.1 Frequent interactions with users, including demonstrations

Meetings were conducted between users and developers in almost all cases in this study, and in most cases, they were conducted frequently throughout development (see **Table J-1 in Appendix J**) Meetings between the developer and the user (client) almost always included a demonstration of the system. For the most part, these demonstrations improved user understanding of the system, its capabilities, and its limitations. They were also an opportunity to collect feedback from users. In case 3 (Watson), the system was demonstrated to leadership before embarking on the project, and to users several times throughout system training and implementation. Demonstrations showed system performance and capabilities. In case 4 (NeuroYou), technical developers discovered early on during development that they needed to include user expertise and knowledge in the system. They demonstrated preliminary versions of the system to hiring managers and HR specialists to collect input for further steps. These demonstrations improved the HR practitioners' understanding of the system and their understanding of the need to include certain data points. In case 5 (ShipCo), the system was developed in close collaboration with the analysts who would use the output and the Researcher whose work the system was designed to automate and ultimately replace. The group met regularly throughout development to demonstrate system performance. These meetings served to demonstrate the system's performance and plan the next phase of development and implementation. In case 6 (Readmission risk), the developers met frequently with the care team and clinical manager during ideation and provided several demonstrations of early versions of the system. These meetings were designed to demonstrate system performance, collect user feedback, and explain development decisions. In case 7 (Low bed tool), the developers met frequently with the Clinical manager (user) to identify a use case for the system, demonstrate early system performance, and collect feedback to adjust the system. In case 8 (Sepsis Watch), the technical developers worked closely with clinicians throughout development and implementation. Prior to implementation, the system underwent a three-month “silent period” during which clinicians validated system output. Weekly meetings were held between developers and clinicians before the “go live” period. These meetings helped ensure the system met the needs of users and respected clinical requirements. In case 11 (CleverLoan), the system was demonstrated multiple times: during ideation to develop the system use case; during development to show technical progress and performance; and after the system was implemented, to explain the need for additional data collection. In case 12 (Rayfood), interactions between the technical developers and the end users served to clarify data questions.

User demonstrations did not always occur or occur at the right time. In case 9 (Anamnesis), only one user demonstration was mentioned, of a completed pilot version of the system. This demonstration showed the capabilities and limitations of the system. The intended users (physicians) expressed multiple reservations, and the system implementation was halted after the demonstration. In case 1 (CAS), user demonstrations were not mentioned. The importance of the work of the intelligence officers (the system users) emerged during system implementation. However, from the description of the case, it does not appear that preliminary versions of the system were demonstrated to intelligence officers. In case 10 (Robodebt), development and implementation went ahead with limited interaction with end users. There was no mention of user demos in case 2 (COMPAS), so it is not possible to assess whether they occurred, their purpose, or their outcome. As the examples above show, for user demonstrations to be useful for system development, the developers need to demonstrate openness to integrating user- or domain-driven change.

3.4.2.2.2 Developers open to integrating user- or domain-driven change

In some cases, the developers appeared very open to integrating user- or domain-driven change (see **Table K-1 in Appendix K)**. In case 4, developers initially thought they could develop a better system by ignoring domain expertise but quickly learned that integrating domain expertise would favour client acceptance of the system. They therefore willingly integrated feedback from the HR specialists and the people analytics team regarding which variables to include or exclude, so the system would best reflect the client organization's values and priorities, even though, according to the developer, this compromised the performance of the system. In case 5 (ShipCo), the data scientist, the CDO, and the researcher worked closely together throughout development, sharing preliminary versions with the broker (end user). The technical developers integrated the broker's feedback to ensure the system met his needs. In case 6 (Readmission Risk Tool), the developers were keen to integrate feedback from users as users defined target use cases and provided suggestions to make the tool more relevant. In case 7, the idea for the tool itself came from a suggestion by a potential user. The developer indicated that in this case, he needed to "get out of the chair" and talk to the user to understand the context to develop a useful system. In case 8 (Sepsis Watch), the technical developers actively sought input from clinicians to ensure the system met the clinical needs. In case 11 (CleverLoan), the bank wanted certain parameters to be included and excluded, such as personal information like religion, sexual orientation, or political mindset, as the bank did not want to discriminate based on these characteristics. The provider of the Rayfood system (case 12) wanted to ensure parameters and data labelling were correct, so they actively sought out input from the client.

In three cases, end-user changes were refused or ignored. In case 1 (CAS), when the intelligence officers suggested the developers change their method for calculating timeframes to match police operations or shared that the system was making nonsensical predictions, like predicting car theft in a no-parking zone, the developer refused to adapt the system. In case 9 (Anamnesis), the feedback from physicians was not integrated into a further iteration. Instead, the implementation was postponed indefinitely. In case 10 (Robodebt), concerns raised by Centrelink staff before the system implementation were ignored by management.

3.4.2.2.3 Integrating knowledge from SMEs

In many cases, developers are experts in statistical models or machine learning approaches, but not in the domain of the system they are to develop (see **Table L-1 in Appendix L)**. To overcome this, Subject Matter Experts (SMEs) are often involved in the development of an AI system. SMEs are specialists in the domain of the system who provide insight when developing the system to ensure it represents the domain of interest. They can be internal employees or external experts, and they can be system users or other organizational stakeholders. SMEs were involved during system development in several cases. In the cases in this meta-synthesis, the role of the SME was to represent and contextualize expert knowledge of the system domain for the development team. They may take the place of end users during development, like the role of the Product Owner in agile development, or they may provide additional insight beyond what the users can provide. Often, this insight is gained during user demos.

In case 3 (Watson), SMEs were the content managers, responsible for initial question set curation and maintenance of input data. They were selected because of their extensive knowledge of a given aspect of Deakin University. Engaging content managers in this way helped ensure source data remained up to date and accurate for future use by Watson. At ShipCo (case 5), the researcher and brokers were asked to resolve edge cases and to provide insight about shipping data to inform system development. In case 7, the end user was engaged in several discussions to ensure the final tool met her needs. In case 8 (Sepsis watch), front-line clinicians were involved in the design and development of the AI system, the user interface, and the new workflow, to ensure the system met their needs and clinical requirements. In case 11 (CleverLoan), the ML provider engaged with the bank to understand their loan approval process and practices, to best integrate them into the CleverLoan system. At Rayfood (case 12), the project leader's background in children's nutrition informed development of the system, to ensure it captured relevant information for school food programs. In the Anamnesis case (case 9), the hospital medical director was on the project team and acted as the product owner; however, it was not clear from the case how recently the medical director had practiced as a physician, and therefore how well he could represent the interests of the physicians impacted by the system.

3.4.2.3 Approaches used during implementation

Following development, AI systems get implemented into organizations. Four approaches to managing implementation were noted in the cases in this study to manage the implementation of AI systems. They were encouraging AI and data literacy of non-technical employees; redesigning workflows in response to system insights and outputs; creating the role of knowledge brokers to translate the AI system output to make it usable by organizational stakeholders; and actively black-boxing the technology, or deliberately hiding technical details of the system from clients or users. Not all approaches were used in all cases, as is described below.

3.4.2.3.1 Encouraging AI and data literacy of non-technical employees

Specific technical expertise is required to develop and implement AI systems, including the ability to understand and curate data, build AI models, and manage the AI pipeline. In addition to technical expertise, an organization benefits from AI systems when non-technical employees have high data and AI literacy. Whether organizations choose to implement an existing system, outsource development of a custom system, or develop a system in-house, increasing the AI and data literacy of non-technical employees can help the system achieve organizational objectives, as was shown in several cases in this meta-synthesis (see **Table M-1 in Appendix M**). Encouraging AI and data literacy means facilitating or providing training or otherwise encouraging non-technical employees to learn about AI and data. In case 2 (COMPAS), in preparation for the implementation of the COMPAS tool, the National Institute for Corrections helped criminal justice actors learn to interpret statistics and choose risk assessment tools. In case 3 (Watson), subject matter experts were taught how to write content for use by an AI system (vs. for publication online), ensuring the system would best be able to use it when responding to student questions. In case 4 (NeuroYou), the client MultiCo provided training courses on data and statistics to HR professionals. As a result, the HR professionals could offer suggestions to developers and have direct influence on which variables to include in the NeuroYou system, ensuring that the skills and attributes measured reflect the values and priorities of the organization. When the developers of the Readmission Risk Tool (case 6) noticed that the care managers did not understand why the tool could not easily provide risk categories, they explained how the AI system made predictions and arrived at a risk score. This helped care managers better understand the system's output and informed the creation of appropriate risk categories.

In two cases, the attempts to increase AI and data literacy of non-technical employees fell short of what the organization needed or wanted, due to limited openness on the part of developers. In case 1 (CAS), the data scientists shared the variables used to develop the system with the intelligence officers, but this was not enough for the intelligence officers to confidently understand and interpret the system output. In case 11, the desire to improve AI literacy was self-driven. The bank management approached internal IT staff to explain the basics of machine learning and related techniques. The developer, however, did not share details of the system with the bank employees or management.

3.4.2.3.2 Redesigning workflows

When an AI system is implemented, the new insights provided by its advanced analytics capabilities can improve decision accuracy but may also change organizational processes and the workflow of the users or the people whose work is impacted by the system's output. This was demonstrated in several cases in this study (see **Table N-1 in Appendix N)**. In the CAS case (case 1), intelligence officers were instructed to pass on the AI system's analytics to police managers to plan resource allocation. However, as the raw system output was not interpretable, the intelligence officers needed to engage in contextualizing and interpreting the system output in their workflow. The introduction of the Sepsis Watch (case 8) system prompted a redesign of the workflow of both the nurses and the ED physicians: nurses needed to respond to alerts from the system by contacting physicians, and physicians needed to respond to calls from the nurses. The Anamnesis system (case 9), if it were implemented, would have seen initial intake and documentation conducted by the AI system, requiring a significant change in the patient intake workflow. By automating the loan approval process, the CleverLoan system (case 11) dramatically altered the workflow of loan consultants, reducing their administrative and cognitive tasks. This freed consultants up for other tasks and made it easier for junior employees to become consultants, but also negatively impacted the role identity of experienced consultants. The workflow redesign in case 2 (COMPAS) was limited to adding the COMPAS assessment to the arraignment process. In case 4 (NeuroYou), insights provided by the AI system indicated an anchoring bias in hiring decisions, prompting a review of hiring practices. It was not clear from the case description, however, if these changes were implemented.

3.4.2.3.3 Integrating knowledge brokers

The role of a knowledge broker is important after the system has been implemented and once it is being used. A knowledge broker plays a mediation or interpretation role between the AI system output and an organizational stakeholder who needs to use the output, often also contextualizing the system output. Knowledge brokers were present in three of the cases in this study (see **Table O-1 in Appendix O**). In the NeuroYou case (case 4), a "people analytics" team was tasked with interpreting the system output to facilitate its use by hiring managers. This team possessed data analytics skills and understanding of the MultiCo hiring process. This team was responsible for analyzing the system output, translating terminology from what was generated by the NeuroYou system games to what was used at MultiCo, and producing visualizations to communicate output to hiring managers, thus facilitating the interpretation and usability of the system output by the hiring managers. In the Sepsis Watch case (case 8), the Rapid Response nurses were the knowledge brokers. A Rapid Response nurse (informally referred to as a "sepsis watch nurse) was responsible for monitoring the Sepsis Watch system and informing ED physicians which patients were at high risk of sepsis. Part of this role involved reviewing the patient's chart to contextualize this identification. Sepsis Watch nurses received training on how the system worked, but were not necessarily technical experts. While the integration of the Sepsis Watch nurse did not increase the explainability or reduce the opacity of the AI system, the additional context provided to ED physicians helped increase their trust in the system's output. Sometimes, knowledge brokers engage in brokerage despite the limited interpretability of an AI system. In the CAS case (case 1), intelligence officers interpreted and contextualized the raw system output to transform it into usable information for the police managers. Doing this required incorporating additional data sources and being creative, rather than relying on being able to interpret the AI system's outputs.

3.4.2.3.4 Black-boxing the technology

One strategy adopted in some of the cases was to actively black-box the technology or refuse to share details about how it worked. In three cases, developers emphasized system performance to convince users of its merit rather than attempting to explain it or reduce its opacity (see **Table P-1 in Appendix P).** In case 3 (Watson), some technical details were shared with the Deakin University IT team to ensure smooth operation of the AI system, but many proprietary details were not divulged. Instead, the IBM team focused on system performance. In case 8 (Sepsis Watch), the developers (including physicians) argued that because sepsis as a condition is complex and its causes are not well understood, an AI system that predicts sepsis does not need to be explainable as long as it performs well. Because this system was deployed in a health-care context, the model details were made public (evidence of transparency), but no effort was made to reduce opacity or increase explainability. Instead, model performance was used to convince hesitant physicians to adopt the system. In case 11, as the development of the CleverLoan system progressed, the system became increasingly opaque. Reports in the publications about this case indicate that as time passed, the developers were less willing to share details of the system, and that the client (bank manager) also appeared less interested in understanding how the system worked, as they were pleased with system performance and the financial and organizational benefits it generated. Some loan consultants, however, expressed frustration with not being able to convincingly explain to a customer why a loan was refused.

Black-boxing the technology was also used in case 1 (CAS). In this case, the developers firmly believed that data science work and police knowledge were fundamentally different, and therefore, they did not need to share model details with intelligence officers. Furthermore, they stated that the complexity of the AI system extended beyond human reasoning and did not make any effort to explain the system to intelligence officers or assist them in their interpretation of system output. As a result, the intelligence officers developed a workaround using additional, interpretable data sources, instead of relying on the CAS's predictions when producing their reports for the police managers.

3.4.2.3.5 Mandating or strongly encouraging AI system use

Once a system has been implemented, it must be used for an organization to benefit from it. In the cases in this meta-synthesis, two approaches were used to ensure use of the system: mandating use and strongly encouraging use (see **Table Q-1 in Appendix Q**). In the Sepsis Watch case (case 8), the system became integrated into ED operations. After implementation of the Robodebt system (case 10), it took over manual calculation of debt overpayment and recovery activities. At the end of the CleverLoan project (case 11), using the system was mandatory for all loan consultants, regardless of experience or expertise. Use of the COMPAS system was not mandatory but was highly encouraged. Judges reportedly routinely asked if a COMPAS assessment had been completed during court proceedings.

3.5 Discussion

In this study, we sought to understand how organizations manage the development and implementation of AI systems. Our analysis uncovered patterns that suggest that the characteristics of AI had an impact on development and implementation, and that multiple approaches were employed to address the impact of these characteristics. Successful projects followed an iterative phased approach and were conducted by multidisciplinary teams. Dataset curation was demonstrated in all successful cases, and a lack of dataset curation limited the success of the AI system implementation. User demos, openness to integrating user- and domain-driven change, and integrating knowledge from SMEs, were used to manage the development of AI systems, whereas encouraging AI and data literacy of non-technical employees, redesigning workflows, integrating knowledge brokers, and black-boxing the technology were strategies used to manage the implementation of AI systems.

During the analysis of the cases in this meta-synthesis, several patterns emerged that appeared to connect tactics for managing AI development and implementation with challenges related to characteristics of AI systems (see **Table 3-6** below for a summary of these patterns, and **Tables H to P** in the appendix for detailed evidence). While evidence for all 11 actions or practices was found in the cases, our analysis of evidence from the cases uncovered how seven of these actions were employed to respond directly to the characteristics of AI. In most situations, evidence from the cases indicated how a specific tactic mitigated the negative impact of a given characteristic of AI. The cases where this occurred appear by number in **Table 3-6** below. In some cases, the evidence indicated that because a given tactic was not employed, the negative impact of a characteristic of AI was not mitigated, which in turn negatively impacted the implementation of the system in some way. The cases where this occurred are indicated in italics and preceded by a "-" in **Table 3-6** below.

Table 3-6 Approaches Used to Respond to Characteristics of AI When Managing Development and Implementation of AI Systems

	Approaches to managing development and implementation of AI							
Characteristics of AI systems	Phased development	User demos	Dataset curation	Subject Matter Experts (SMEs)	Knowledge brokers	AI and data literacy	Developer openness	Black-boxing technology
Inscrutability		5, 6 *-9*			4, 8 *-1*	4, 6, 8 *-1, -11*	4 *-1*	3, 8, 11 ***1****
Learning-driven data dependency			1, 2, 3, 4, 5, 6, 7, 8, 11, 12 *-9, -10*	3, 4, 5, 8, 12 *-10*		3, 6	12 *-10*	
Learning-driven unpredictability	4	4, 7		4			4 *-11*	
Autonomy		3 *-9, -10*					*-9*	

Note: Three tactics (Multi-disciplinary teams, Workflow redesigns and Mandating use) appeared frequently in the cases included in this meta-synthesis but based on the evidence provided in the published case studies were not connected directly to addressing characteristics of AI systems. For that reason, those three tactics were not included in this table.
*In case 1, black-boxing the technology was applied, but was not effective in addressing inscrutability.

Organizations wanting to implement AI should develop the AI and data literacy of non-technical employees, as this can help address challenges related to the inscrutability of AI systems and improve the quality of the data used to train and support the AI system. When knowledge brokers are integrated into organizational workflows using outputs of AI systems, they can play an important role in addressing the interpretability of AI systems, a dimension of inscrutability. In cases where the inscrutability of the output of an AI system does not directly impact organizational operations, developers can consider black-boxing the technology and instead emphasize system performance to address inscrutability of AI systems and enable organizations to gain value from their AI systems. Carefully curating the dataset during both development and operations of an AI system helps address challenges related to learning-driven data dependency. Finally, while the benefits for software development in general of phased, iterative development, conducting user demonstrations, and developer openness to user- or domain-driven change are well understood, these tactics helped address characteristics in many ways, by enhancing transparency, explaining and addressing unpredictability, and providing opportunities for users to raise concerns regarding system autonomy. Below we explain how these tactics allow organizations to address the challenges posed by AI characteristics.

3.5.1 How organizations can address inscrutability

The ability to understand and explain how a system arrives at a conclusion is important for user and stakeholder trust, and for system usability (Von Eschenbach, 2021). However, AI systems are inscrutable by nature (Berente et al., 2021; Burrell, 2016). Therefore, organizations wanting to implement AI must find a way to address inscrutability. One strategy to address inscrutability is explainable AI (or XAI). XAI refers to developing models in a way that reduces their opacity and focusing on transparency by sharing model parameters (Coussement *et al.*, 2024; Ding *et al.*, 2022). This meta-synthesis uncovered four alternative tactics organizations can adopt to address the inscrutability of AI. Three of these tactics helped address inscrutability by focusing on interpretability. These were integrating knowledge brokers; encouraging AI and data literacy of non-technical employees; and holding frequent meetings with users including demonstrations. In three of the successful cases, instead of reducing inscrutability, the developers emphasized performance and black-boxing the technology.

The ability to share knowledge between diverse groups of actors is a key organizational competence (Pachidi *et al.*, 2021). However, effectively sharing knowledge can be hindered by "semantic boundaries," as groups may possess specialized knowledge or require a specific skillset to understand and use their knowledge (Carlile, 2004). Knowledge brokers are a type of boundary spanners, or people who can cross these semantic boundaries (Levina et Vaast, 2005). In AI development, integrating knowledge brokers facilitates the transfer of knowledge between the AI developer community and the user community, as each group possesses specific knowledge relevant to the system's success. Their role can therefore be relevant in addressing inscrutability of AI systems, as they can translate the AI output into information relevant and usable by another group. The examples of knowledge brokers in the cases in this meta-synthesis were neutral third parties that do not belong to either group (e.g., case 1, CAS[15] and case 4, NeuroYou), and members of one group who develop specialized skills in knowledge transfer to be able to cross the semantic boundary (e.g., case 8, Sepsis watch). However, while knowledge brokers can help address inscrutability in some situations, this appears more likely when the knowledge brokers are supported in their role. In the NeuroYou case (case 4), a people analytics team was formed to assist in interpreting the system output, helping to address system inscrutability, In the CAS case, however, the knowledge broker role and the specific activities emerged at the initiative of the intelligence officers, not through top-down direction. Furthermore, the intelligence officers appeared left to learn on their own; the data scientists did not support them or listen to their concerns and feedback, and instead actively black-boxed the technology. When it comes to complicated technology like AI, neglecting basic training or not offering support can have the reverse effect, where employees creatively interpret statistics and do not properly mobilize the insights provided by the AI system, compromising the reliability of the insights provided by the system and limiting organizational benefits. Alter (2014) notes that impacts of workarounds include impacts on subsequent activities and non-compliance with management intentions. A workaround is defined as:

> a goal-driven adaptation, improvisation, or other change to one or more aspects of an existing work system in order to overcome, bypass, or minimize the impact of obstacles, exceptions, anomalies, mishaps, established practices, management expectations, or structural constraints that are perceived as preventing that work system or its participants from achieving a desired level of efficiency, effectiveness, or other organizational or personal goals" (Alter, 2014, p. 1044).

A second way to reduce inscrutability is to improve interpretability by encouraging AI and data literacy of non-technical employees. AI and data literacy has been identified as a key skill for enabling organizational value generation from AI (den Hamer *et al.*, 2024). Unlike user training, which often focuses on ensuring users know how a system works and can operate it according to organizational needs and objectives, AI and data literacy involves increasing the general understanding about AI systems of non-technical organizational stakeholders. Interpretability of AI systems refers to the ability of users of the system's output to relate the output to their understanding of their context (Berente et al., 2021). Therefore, to address

[15] In case 1, knowledge brokers (intelligence officers) were used to address system inscrutability. While they provided the police managers with useful information, as this information was derived from alternate sources and not the system itself, they did not reduce the inscrutability of the system.

inscrutability when implementing AI systems, user training may need to go beyond how to use the system, and incorporate basic explanations of statistics, probability and machine learning, as well as the relationship between data quality and AI system output (e.g., Blok *et al.*, 2021; Rane, Choudhary et Rane, 2024). In the cases in this study, approaches adopted to encouraging AI and data literacy included providing lengthy and detailed explanations of the variables used in the model embedded in the system (case 4, NeuroYou); and ensuring users understood how the system produced its output, and why it was challenging to translate the output into categorizations (case 6, Readmission Risk Tool).

One tactic used in the cases in this study to address inscrutability involved actively black-boxing the technology, instead focusing on the performance of the system. In some cases, highlighting the tangible benefits of AI, such as its potential to increase process efficiency or organizational performance, may allow organizations to bypass the need to address inscrutability. This challenges literature that indicates that understanding of how a system works is critical for developing trust of individual users (Von Eschenbach, 2021). It also contradicts research that notes that a shared understanding of what a system does or how a system works is crucial for successful outsourcing (e.g., Gregory, Beck et Keil, 2013). The cases in this study demonstrated that black-boxing the technology can be effective when being able to understand the system does not directly relate to being able to effectively use its output (e.g. case 3, Watson), even in high-stakes contexts such as medical diagnosis (e.g. case 8, Sepsis Watch). In certain cases, pressure to improve organizational performance can be more important than understanding how a system works, such as in case 11 (CleverLoan). In all these cases, focusing on system performance instead of reducing inscrutability was a way to transcend explainability (Mayer et al., 2024). However, when the system performs tasks that involve relevant skills or organizational knowledge (such as the CleverLoan system), black-boxing the technology may have downstream implications due to loss of critical thinking skills and expertise(George, Baskar et Srikaanth, 2024), and loss of organizational knowledge (Mayer et al., 2020), and the long-term implications of this potential loss of skills and knowledge were not assessed in the cases in this study.

Research has demonstrated that involving users in the development and implementation of information systems helps favor success (Barki et Hartwick, 1994; Hylving et Bygstad, 2019; Wagner et Newell, 2007; Wagner et Piccoli, 2007). Agile development methods have demonstrated that one way to ensure involvement is by conducting development and implementation in phases, punctuated by frequent user demonstrations after key phases in development and implementation (Hassani-Alaoui, Cameron et Giannelia, 2020; Heikkila *et al.*, 2017). Previous research on IS development suggests that vendor willingness to integrate user feedback positively influences knowledge transfer from the developer to the client, and subsequent ISD success (Ko, Kirsch et King, 2005; Teo et Bhattacherjee, 2014). In the case of AI implementation, user demonstrations conducted between phases of development can be used as an opportunity for developers to identify and address interpretability challenges (e.g., case 5, ShipCo and case 6, Readmission Risk Tool). When developers do not demonstrate frequently, or are unwilling to integrate feedback regarding inscrutability, implementation can be compromised. In one case (case 9, Anamnesis), employees (physicians) resisted system implementation. Employee resistance can be productive when it highlights problems with the system and when implementers are open to integrating user- and domain-driven change and respond by rectifying the source of the problems. However, when users or stakeholders raise concerns, but implementers either do not respond or provide a response that is incongruent with these concerns, system implementation can be compromised (Rivard *et al.*, 2012). Developers and implementers of AI systems should be attuned to user concerns and open to integrating their feedback to address inscrutability of AI.

3.5.2 How organizations can address learning-driven data-dependency

AI requires data to learn patterns during development, and to apply and refine these patterns once deployed (Lebovitz, Levina et Lifshitz-Assaf, 2021; Priestley *et al.*, 2023; Vial *et al.*, 2021). However, perfect data is rarely available (Cai *et al.*, 2015). It is therefore unsurprising that all projects in this meta-synthesis faced challenges with learning-driven data-dependency. To address the learning-driven data dependency of the AI systems during both development and deployment, companies should engage in ongoing dataset curation and development of AI and data literacy of non-technical employees, and development teams should be open to integrating user-and domain driven changes and involve subject matter experts (SMEs). A careful approach to curating the data specific to training and operation of the AI system positively impacts system accuracy, relevance, and performance. Successful dataset curation goes beyond simply collecting and accessing data relevant to system predictions. It includes assembling existing datasets for training, codifying tacit organizational knowledge for use by the AI system, and ensuring ongoing data quality, including accuracy and relevance. Failing to include all relevant contextual data limits a system's ability to make contextualized predictions, limiting its usefulness in an organizational situation where context is key. Improperly assembling datasets, such as incorrect alignment of formats of input data, impairs the system's ability to make accurate predictions. Codification of tacit organizational knowledge is often required when an AI system is developed to engage in or support cognitive tasks (Lebovitz et al., 2021). While this is not an easy task, neglecting this codification can result in a system that does not meet user expectations, and may compromise system implementation.

As AI systems are socio-technical systems involving users and the technology (Asatiani *et al.*, 2021), improving the AI and data literacy of non-technical employees can also address the learning-driven data-dependency of these systems (e.g., Rane et al., 2024). In many organizations, non-technical employees are responsible for ensuring the quality of input data for the development and ongoing operation of an AI system, such as in the Watson (case 3) and Readmission Risk Tool (case 6) cases in this study. Employees involved in these activities are not required to understand the nuances of statistics and probability involved in system predictions. However, because they are managing the data that will be used by an AI system, they play a crucial role in ensuring data quality. In such cases, providing targeted training that focuses on understanding the link between data quality and system performance can help improve the quality of input data used by the AI system to make predictions, thereby contributing to the improvement of the performance of AI systems. While IS research has extensively examined how to train employees to use an information system (e.g., Kang et Santhanam, 2003; Orlikowski et Hofman, 1997; Venkatesh *et al.*, 2003), this study highlights the importance of AI and data literacy training for supporting system accuracy and relevance.

Developer openness to integrating user- or domain-driven changes, often facilitated by including subject matter experts (SMEs) can also positively influence AI system development and implementation by addressing learning-driven data-dependency. In the Rayfood case (case 12), developer openness to integrating user- and domain-driven changes led to increased system accuracy and performance. On the contrary, in the Robodebt case (case 10), despite issues raised by users regarding the approach to dataset curation, a lack of openness to integrating these changes on the part of the developer and sponsoring organization meant that these issues were not addressed. Furthermore, in several cases in this study, inclusion of SMEs facilitated data collection, curation or cleaning in various ways, helping to address learning-driven data-dependency. In the Watson case (case 3), content experts ensured ongoing data quality to maintain system performance during operations; in the NeuroYou case (case 4), HR experts informed data collection for initial model training and created data by codifying hiring decisions to further fine-tune the model; in the ShipCo case (case 5), experts helped resolve "edge cases" to ensure improved operation of the algorithm; and in the Sepsis Watch case (case 8), clinician involvement throughout ensured that the context of sepsis detection and treatment and the hospital environment were considered during development. In the Robodebt case (case 10), ignoring domain experts' concerns regarding data quality resulted in a sub-optimal system that mis-calculated debts. Prior research has demonstrated the importance of collaborating with the customer for success in software development (Maruping et Matook, 2020; Serrador et Pinto, 2015). This research highlighted the role that integrating user- or domain-driven change can play in addressing data dependency during AI system development. Guidelines for how to integrate subject-matter expertise during system development include supporting interaction between human users and the problem the system is designed to address early and often, sharing control of development, focusing on usability and user experience, and promoting mutual learning and support (Fischer, Nakakoji et Ye, 2009; Silva et Araújo, 2024). This study builds on previous research by demonstrating that the involvement of subject matter experts can address the learning-driven data-dependency of AI systems.

3.5.3 How organizations can address learning-driven unpredictability

Closely related to learning-driven data-dependency is the inherent unpredictability of AI systems, driven by the fact that these systems are based on statistical probability and learn from data during both development and operation (Berente *et al.*, 2021). This unpredictability can negatively impact system acceptance and use, particularly in situations where a system designed to automate cognitive work produces output misaligned with the conclusions of the employees who conducted this work prior to system implementation. To overcome challenges related to learning-driven unpredictability, developers should provide frequent demonstrations of interim versions of the system and ensure involvement of subject matter experts throughout development and implementation and organizations should take time to understand user perception of unpredictable output and its potential impact on system acceptance and use. This can be achieved through breaking development and implementation into phases and conducting frequent user demonstrations. While one focus of user demonstrations in software development is to communicate the purpose of the system and test the usability of its user interface, for AI systems, these demonstrations are also an opportunity for users to identify what aspects of system outputs are surprising, and to raise concerns. This is closely related to the goals of explainable AI, to help users understand how an AI system makes predictions or arrives at an output (Ding *et al.*, 2022). While it may not always be possible to address all drivers of AI system unpredictability, when coupled with developer openness to integrating user-driven changes, user demonstrations help identify the most pressing issues and provide direction for system development. For these user demonstrations to be useful for developers, they should occur frequently during development and implementation. Similarly, involving subject matter experts throughout development and implementation can help address learning-driven unpredictability challenges. In many contexts, SMEs validate requirements of a proposed system and can evaluate functionality (Silva *et al.*, 2024). This study suggests that in the case of AI systems, SMEs can provide contextual awareness to AI developers, explain the impact of unpredictability and motivate developers to understand its drivers. Previous literature has examined the role of the product owner in agile ISD teams as a representative of the customer's interest and an intermediary between the customer and the development team (Bass *et al.*, 2018). This research demonstrates how SMEs provide key insights regarding AI system development and operations, helping to reduce the unpredictability of these systems.

3.5.4 How organizations can address autonomy

Many AI systems are designed to operate autonomously, automating all or part of a workflow in an organization. System autonomy can impact human oversight capabilities, workflows, and the way humans and machines interact (Berente *et al.*, 2021; Mayer *et al.*, 2020; Rinta-Kahila *et al.*, 2022). These impacts may be more significant when the system directly impacts the core business or operations of an organization. In such cases, organizations intending to implement systems designed to operate autonomously must be aware of these potential impacts and plan to mitigate them. Meetings between developers, users and other stakeholders provide opportunities not only to demonstrate how a system works, but to collect feedback on risks perceived by end users and other stakeholders, including autonomous operation of an AI system and potential impacts the system may have on oversight, workflows, and human-machine interaction. Similar to addressing inscrutability, for these meetings to be useful in addressing autonomy challenges, however, developers must be open to listening to and responding to employee concerns regarding autonomy of the system. Knowledge workers whose work is destined to be automated by a system are well placed to understand all aspects and implications of their work and can therefore provide relevant critiques of proposed AI-driven automations, such as responsibility and accountability for system decisions; override capability for system errors; and long-term risks of loss of expertise and organizational knowledge. When test or pilot versions of a system are not demonstrated, such as in the Robodebt case (Case 10), or demonstrated too late in the development trajectory, such as in the Anamnesis case (Case 9), users and other stakeholders cannot provide feedback, which can hinder early identification of risks of autonomous systems. When employee concerns are ignored, organizations risk losing sight of long-term implications of AI implementation.

3.5.5 Contributions and implications

This meta-synthesis makes three contributions, both empirical and theoretical, with implications for both research and practice (Agerfalk *et al.*, 2020). The first contribution is a more complete understanding of how this process is managed across a broad range of contexts. These insights provide empirical grounding for future theorization and improved understanding for practitioners on how AI development and implementation unfold. The second contribution is an increased understanding of how and why the implementation of these systems differs from that of other types of IS. The third contribution is theoretical arguments and empirical evidence of how specific practices can be adopted during development and implementation of AI systems to address the challenges stemming from the characteristics of AI. Each of these contributions is presented in detail below.

The first contribution of this study is a more complete understanding of AI development and implementation. By examining detailed accounts of AI development and implementation through an interdisciplinary meta-synthesis of qualitative case studies, this study offers a more complete understanding of AI development and implementation. Previous studies have suggested the strategic potential of AI across various contexts and use cases (e.g., Borges *et al.*, 2021) but do not provide a detailed description of the implementation process. Practitioner articles provide many suggestions and examples of how AI can be used in organizations (e.g., Mithas, Murugesan et Seetharaman, 2020) but fall short of detailed analysis of how development and implementation are managed. This study synthesizes empirical examples of this contextual and use-case diversity, providing further evidence for the potential breadth and scope of AI use in organizations. Through synthesizing accounts of various AI implementation initiatives across contexts, this study found that AI development and implementation follows one of many hybrid phased/iterative approaches. This echoes previous research specific to ML deployment that noted that there are key phases in the workflow but that they do not follow a pre-specified order and provides evidence for multiple potential successful combinations of phases and actions (Paleyes *et al.*, 2022) and provides empirical evidence of multiple paths that AI implementation can take. These insights provide empirical grounding for future theorization on the management of the development and implementation of AI systems. For example, future research could explore if and how the order or iteration of specific phases in AI development and implementation affects project outcomes. The insights of this study can also inform practice. The synthesis of empirical accounts of case studies provides suggestions for practitioners on how to manage their AI development and implementation initiatives.

The second contribution of this study is a confirmation that the characteristics of AI systems – inscrutability, learning-induced data dependency, learning-induced unpredictability, and autonomy (Benbya *et al.*, 2020; Berente *et al.*, 2021; Schuetz *et al.*, 2020) – can impact development and organizational implementation of these systems. Previous literature has noted that these characteristics distinguish AI systems from previous types of information systems, and suggested that these differences may impact how AI systems are developed, implemented and used (Berente et al., 2021; Schuetz & Venkatesh, 2020). This meta-synthesis provided interdisciplinary empirical grounding for an explanation of ways in which the characteristics of AI impact system development and implementation in organizations. As such, this study contributes to extant research on IS implementation by extending theoretical understanding of challenges specific to AI implementation. For example, extant theories on resistance to IS implementation suggest that resistance can occur due to perceptions of threats attributed to the system (Lapointe *et al.*, 2005; Marakas et Hornik, 1996; Silva et Backhouse, 2003), changes job characteristics and responsibilities (Bala et Venkatesh, 2013), or technical difficulties experienced after implementation which can undermine confidence in the system (Ortiz De Guinea et Webster, 2013; Saatçıoğlu Ömür, 2009). This meta-synthesis revealed that across contexts, it is the inscrutability, the learning-induced unpredictability and the autonomy of AI systems that can lead to user distrust of these systems. The implication for research of this finding is that researchers seeking to understand the management of AI development and implementation should pay close attention to how organizations anticipate and address employee distrust of AI systems arising from these characteristics.

The third contribution is theoretical in nature. The qualitative synthesis of the literature conducted in this study allowed for deeper understanding on how organizations address the impact of characteristics of AI, i.e., how they manage development and implementation of AI systems to gain value. Single case studies provide detailed portraits of one case of development and implementation but lack an overarching view. Extant literature reviews on AI development and implementation list challenges and potential strategies without connecting them (Enholm *et al.*, 2022; Lwakatare *et al.*, 2020; Paleyes *et al.*, 2022). Using a qualitative meta-synthesis approach, we were able to infer a process perspective of development and implementation, tying the challenges arising from characteristics of AI to development and implementation actions. The synthesis of findings across studies allowed us to suggest relationships between impacts of AI characteristics and mitigation strategies. For example, previous literature has suggested that inscrutability, or limited model interpretability and explainability, causes challenges when deploying machine learning in an industrialized setting (Lwakatare *et al.*, 2020). Others have noted that using simple models early in development may help facilitate interpretability (Paleyes *et al.*, 2022). Our study revealed that multiple strategies can be employed to address inscrutability, sometimes reducing it, sometimes transparently explaining why it does not need to be reduced, and sometimes by demonstrating performance to overcome the need to address inscrutability. Similarly, previous studies have found that because AI systems are dependent on data to learn and operate, data quality is directly tied to the ability of an AI system to provide reliable predictions (Enholm *et al.*, 2022). Data quality issues, including limited access to training data and incompleteness of training data in deployment of ML in industrialized settings can result in low-quality AI systems (Lwakatare *et al.*, 2020). Furthermore, previous studies have noted that machine learning models may drift over time, in seemingly unpredictable ways (Paleyes *et al.*, 2022). In industrial settings, a predictable model development cycle was important (Lwakatare *et al.*, 2020). Suggestions in extant literature for addressing data quality include using synthetic data or automating data validation (Lwakatare *et al.*, 2020), and model supervision and maintenance can address drift and learning-induced unpredictability. This meta-synthesis uncovered the importance of carefully curating the dataset required by the AI system. It also revealed that some data quality issues can be addressed by non-technical employees, when these employees are encouraged to gain skills in data and AI literacy. Extant research refers to the importance of employee participation and involvement in IS implementation (Barki *et al.*, 1994), and that user training helps users understand how to best use a system. This meta-synthesis demonstrated that addressing challenges arising from the characteristics of AI required more than training on system use. Cultivating the in-house expertise of non-technical employees, for example by improving their AI and data literacy, was critical in many of the cases. For researchers, these findings motivate future inquiries into the nature of successful and appropriate AI and data literacy training. For practitioners, this study points towards specific practices and approaches to employee training and support when implementing AI-based systems that can be particularly helpful in addressing challenges arising from the characteristics of these systems.

3.6 Conclusion

This paper presented a qualitative meta-synthesis of twelve published case studies of implementation of AI in organizations. By carefully examining the trajectory of development and implementation of AI systems in organizations, we found that working towards a negotiated system between developers, users and SMEs, and developer willingness to share and solve customer problems were essential to successful AI implementation.

This study is not without limitations. One limitation in this study is that the data available for analysis was only what was published in cases. To overcome this limitation, additional data was sought in multiple publications about the same case or publicly available information. Authors of published cases were contacted to provide additional details, but unfortunately none of them were able to do so. Similarly, the timing of the publication cycle means that what is published in IS journals may reflect systems, issues and practices that may be out of date. This was addressed by searching conference papers, which, due to their shorter acceptance and publication cycle, often report on more recent cases. Third, impacts of implementation of AI systems are felt across multiple levels of an organization. Using published case studies of AI implementation limited the ability to examine these multiple levels and their interaction, as this data was not available in any of the cases included in the study. Further empirical research on the implementation process of AI systems could incorporate a multi-level approach to data collection and analysis to understand the interplay between individuals, groups and organizations. A final limitation is that this study examined cases of top-down driven implementation of AI systems; however, many AI systems are introduced into organizations differently, through the integration of AI capabilities into existing software packages, like integrating Copilot into Microsoft services, for example. Future research should explore how this approach to integration differs from more traditional implementation in how systems are accepted and used by users and how they impact organizations in different ways.

Future research could extend the findings of this study in several ways. Additional empirical studies could empirically verify and validate the proposed relationships between characteristics of AI and mitigation strategies identified in this meta-synthesis. More extensive research can examine to what extent these relationships hold, and in which contexts. For example, knowledge brokers appeared to play an important role in AI system implementation but were not always able to address the inscrutability of these systems. Future research could investigate how this role and associated responsibilities are shaped to directly address challenges arising from AI. Similarly, this meta-synthesis identified several approaches frequently used in developing and implementing AI systems that were not reported to directly address characteristics of AI. Future research could investigate to what extent these approaches are relevant for the development and implementation of AI systems, and if they differ in major ways from how they are used in other software development initiatives. For example, future studies could explore how workflows can be best designed in response to implementing AI systems to counter the effects of challenges arising from their characteristics.

As AI advances (and it advances rapidly) its characteristics may also evolve. It will be important to continue to monitor the unique features of this technology and how they may challenge what we know about IS development and implementation. The cases included in this study were all examples of analytic AI (Davenport et High, 2024), but generative and agentic AI are increasingly being introduced to organizations. Future work could aim to identify which characteristics of other types of AI may influence implementation of these technologies. Furthermore, generative AI may be introduced to organizations in a different manner than the AI systems analyzed in this study, either through embedding in existing applications (e.g., Haki *et al.*, 2025) or through employees "bringing their own AI" (van der Meulen et Wixom, 2024). Future research should consider the different ways these technologies enter organizations to determine if the same impacts and strategies identified in this study still apply.

Empirical work could also explore the long-term implications of AI in organizations, linking them to how AI development and implementation are managed. One finding from this study is that in all cases, when implemented, AI had an impact on the humans in the organization and involved with the organization. Current generative AI systems have the capacity to automate and replace entire positions held by humans. Future research should examine the long-term implications of AI of all types in organizations for employees and organizations (see Hai *et al.*, 2025 for early work on this topic), and determine if the implementation trajectory accentuates or mitigates these impacts.

Finally, research suggests that outsourcing knowledge work to autonomous algorithmic systems risks loss of organizational knowledge and erosion of employee critical thinking skills (e.g., George *et al.*, 2024; Mayer *et al.*, 2020). The cases included in this study focused on development, implementation, and the period immediately following implementation, not the long-term implications of integration of these systems in organizations. Future research could explore the long-term impact of use of AI systems on critical thinking and organizational expertise, and whether attending to early warnings like the reservations expressed by the loan consultants during implementation can mitigate these impacts.

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Conclusion

Many organizations of various types are investing in AI (Davis, 2020; Norrie *et al.*, 2020; Shein, 2025). Although these investments continue to grow (Brethenoux *et al.*, 2024) and success stories are becoming more common (Tamersoy *et al.*, 2025), the path from investment to value generation is not always entirely clear (Ransbotham *et al.*, 2021; Schmelzer *et al.*, 2024). Therefore, this thesis aimed to answer the research question ***How do organizations gain value from AI?*** Three essays were used to examine this research question from three different angles.

Each essay makes several contributions to research and practice. **Essay 1** examines how the fit between organizational factors and IT resources can contribute to organizational value generation from GenAI in the context of religious organizations. This study explores one way to understand opportunities for value generation from AI by applying the existing ISBV framework (e.g., Schryen, 2013) to organizational value from IT in a non-monetary context. While monetary value is often essential for the sustainability of most organizations, non-monetary value is integral for others. This essay provides a better understanding of non-monetary value generation from AI in the context of religious organizations and focuses on one type of non-monetary value: religious and spiritual value. It opens the opportunity for further exploration of alternative conceptualizations of value from IS by extending the ISBV framework to the novel context of religious organizations. It also demonstrates one way to disaggregate the constructs of this framework and proposes a configurational approach to understanding value from AI.

Essay 2 provides insights into how AI development teams cope with the stressors of rapid development of AI in a complex ecosystem. In this study, a single AI project was able to generate value for multiple stakeholders: the client; the developer; and the ecosystem at large. This was made possible through specific project management practices, including socialization of organizations across the project ecosystem, overstaffing and retaining-in-orbit of data science experts, and strategic data assessment blueprinting. This essay provides a rich, contextualized understanding of these three practices. It contributes to a better understanding of the role these practices play in managing AI projects. It also offers opportunities for future theorizing around these three practices.

Essay 3 identifies how the distinguishing characteristics of AI impact its development and implementation. Through an examination of 12 published cases of AI development and implementation projects across contexts and industries, this essay contributes to a better understanding of how organizations can address these challenges, mitigate potential negative impacts from AI, and benefit as much as possible from their AI systems. This essay contributes to practice by identifying the ways in which the characteristics of AI may negatively impact organizational implementation of these systems, and proposing tactics organizations can adopt for managing the implementation of AI to maximize the potential value gains. It contributes to research by providing theoretical arguments grounded in empirical evidence for the influence certain tactics undertaken by an organization can have on managing the challenges arising from the distinguishing characteristics of AI.

Individually and collectively, the three essays of this thesis enrich our understanding of organizational value generation from AI. Organizations of all types can gain value from AI by understanding what AI is – the components and characteristics of the technology, and the data, human actors and practices that make up its sociotechnical system – and how to dynamically configure AI systems and organizational elements. Considering the overarching research question of this thesis – ***how do organizations gain value from AI?*** – the findings and conclusions across the three essays offer several further insights for both research and practice. The following paragraphs outline contributions to research and practice, organized under the three elements of the research question: organizations, AI and value.

Organizations

The three essays of this thesis explore AI development and implementation in a variety of organizations. This thesis showed that AI has the potential to generate value for different types of organizations, demonstrating the relevance of this research question across contexts. In addition, the three essays all suggest that a configuration of multiple elements within an organization is often required for organizations to gain value from AI. Essay 1 highlights how the configuration of the layers of religious authority and the components of GenAI systems allows for religious value generation for religious organizations. Essay 2 demonstrates that the management of an AI project in a complex supply chain ecosystem requires the configuration of data, expertise of team members, and stakeholders across the ecosystem. Essay 3 notes that specific project management practices must be adopted to address specific challenges arising from the characteristics of AI when managing an AI project.

There are four implications for research of this thesis from the perspective of organizations. First, by exploring value generation from AI across diverse organizational contexts, this thesis highlights the relevance of continuing to study AI projects in a variety of organizations. Exploring value generation with AI in diverse organizational contexts can help to both understand how the nuances of each type of organization may influence value generation from AI, and to determine patterns that hold across organizational contexts. Second, this thesis suggests that understanding how organizations generate value from AI can be enriched by adopting a configurational perspective, i.e., by linking organizational elements (e.g., IT resources, strategies, and project management practices) with AI elements (e.g., systems as a whole, their components or characteristics, and AI specialists). Future research should explore how different configurations of organizational elements and AI elements influence organizational value generation from AI in different ways (Ragin, 1987). The third implication of this thesis is a call to consider value generation from AI from the perspective of multiple organizational and extra-organizational actors. In the essays in this thesis, value was conceptualized primarily from the perspective of organizational leadership. However, all three essays showed that AI systems can also generate value for other organizational stakeholders, such as employees, organizational members, or partner organizations (Bell *et al.,* 2023). Future research should continue to explore value generation from the perspective of different organizational stakeholders. Finally, as organizations evolve over time, it is likely that the configuration between organizational elements and AI elements is dynamic. Future research should investigate the drivers and consequences of the dynamic nature of this configuration, to better understand how organizations can adapt the management of their AI initiatives.

The implications for practitioners of the organizational perspective in this thesis are threefold. First, this thesis provides empirical examples of diverse organizations that leveraged AI for multiple use cases. Organizations of all types can take inspiration from this diversity for future organizational implementations of this technology. Second, the findings of this thesis suggest that thinking strategically about AI often involves considering the configurations of multiple organizational elements, such as authority structure, development team members and external stakeholders, or project management practices. Organizational leaders should therefore carefully consider which organizational factors need to be configured and how to best configure these organizational factors and resources with a given AI initiative. Third, as highlighted in Essays 2 and 3, when planning and executing an AI initiative, organizational leaders should consider the challenges that may arise from AI initiatives, and adopt specific practices when managing AI initiatives to address these challenges.

AI

Across the three essays, this thesis examined a variety of types of AI: Essay 1 explored GenAI; Essay 2 examined an NLP system; and Essay 3 included examples of different types of AI, most of which involved machine learning. The definition of AI adopted at the beginning of this thesis and for each of the papers is "*the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems"* (Berente et al. 2021, p. 1435). In this definition, AI is defined primarily as a technology. However, the essays in this thesis recognize that AI is not simply a digital system that users interact with and control. In fact, AI can be an autonomous actor with agency-like properties, such as learning and adapting. While all three essays use the above definition, the propositions and findings of each of the essays further enrich our understanding of AI and reflect aspects of AI beyond those evoked in the above definition. Essay 1 conceptualizes AI as a set of component parts (Hosanager et Krishnan, 2024). This approach allows for a detailed examination of how the components can be individually leveraged and configurationally combined with organizational factors to gain value. Essays 2 and 3 extend the understanding of AI systems beyond the technology alone and conceptualize AI as a sociotechnical system (Makarius *et al.,* 2020). Essay 2's findings broaden the conceptualization of AI to encompass the development team, the data, and the supply chain actors responsible for providing the data. This includes the critical practice of "retaining-in-orbit" of additional data scientists, the role of socialization in enhancing data quality for current and future projects within complex ecosystems, and the contribution of supply chain actors in ensuring and maintaining data quality. Essay 3 highlights that the challenges arising from characteristics of AI that can affect the development and implementation of AI systems involve more than the technology, but also the humans involved in its development and use.

The conceptualization of AI in this thesis has two main implications for research. First, the decomposition of AI into component parts presented in Essay 1 (Hosanager et Krishnan, 2024), while not opening the black box of AI entirely, provides a suggestion of how the individual components of AI can uniquely influence value generation. It opens the possibility for future research to study the influence of individual components of AI systems on organizational value generation, beyond studying the influence of these systems holistically. Second, the sociotechnical perspective of AI that emerged in this thesis suggests that future research on AI in organizations should look beyond the systems themselves, or their implications for organizational actors and organizations, and consider AI systems as complex systems comprised of a configuration of data, technology, humans and practices.

For practice, the decomposition of AI into component parts proposed in Essay 1, and the sociotechnical conceptualization of AI proposed in Essays 2 and 3 can remind practitioners that, like in any IS development or implementation project, AI systems are composed of different elements. Practitioners should consider the extent of control they may have over each of the elements and manage their AI initiatives accordingly. These considerations may include the impact of the choice of foundational model for a GenAI system when developing a customized GenAI tool for their organization, the best approach for improving the AI and data literacy of employees or partner organizations, and how to improve data quality for their AI projects, to mention a few. In addition, practitioners should be aware of the challenges that can arise from the specific characteristics of AI systems and adopt appropriate practices to address them. Finally, learning-driven unpredictability and autonomy, characteristics of AI systems, indicate that AI artifacts have some agency: they are able to learn and adapt and can influence work processes. As such, when planning the integration of AI systems into organizational processes or activities, practitioners should therefore consider AI systems as organizational actors, not just tools used by human actors.

Value

The three essays in this thesis demonstrated that the understanding of value from AI is broad and multi-faceted. Essay 1 focuses on how religious and spiritual value can be generated for religious organizations by GenAI. The AISys system developed in Essay 2 generated multiple types of value for various project stakeholders. BizAI, the organization contracted for the development and implementation of AISys, gained both monetary and reputational value from this project. CityPort and the entire local supply chain ecosystem gained strategic value: the increased awareness of the potential of AI gained through this project stimulated digital transformation across the ecosystem. Furthermore, AISys generated value for society in general by saving lives through the reduction of dwell time of critical cargo. Essay 3 highlights that an organization can only gain value from AI if the AI system is successfully implemented and used within the organization. Through the variety of contexts and use cases studied in the cases reviewed (e.g., process and resource optimization, improved decision-making, improved patient care), Essay 3 further demonstrates that AI has the potential to generate both monetary and non-monetary value.

The focus in this study was on value generation from AI. However, in some situations, the implementation of AI systems results in the delegation of key organizational processes and operations to an AI algorithm, potentially negatively impacting organizational knowledge and expertise in the long term (Reis et al., 2020; Waardenburg et al., 2021). Furthermore, AI has the potential to destroy value for organizations and individuals. Value destruction by AI was demonstrated in one of the cases in Essay 3, where the mis-managed introduction of an AI system designed to automate recovery of welfare overpayment resulted in damage to the reputation of the government driving the initiative and the citizens whose lives and livelihoods were directly impacted by the system's inaccurate calculations and autonomous operation (Rinta-Kahila et al., 2022). In addition, Essay 1 suggests that improper fit between layers of authority and components of GenAI may lead to AI systems that are developed and used in a way that can destroy religious value. For example, when a GenAI system is misaligned with the layers of religious authority, it may produce hallucinations that contradict the ideology of a religious organization, or misrepresentation of religious leadership. This may negatively affect the credibility and reputation of a religious organization, and its ability to generate value for adherents. This in turn could reduce commitment of existing adherents to the organization and impact recruitment of new adherents, limiting organizational growth and value generation.

The insights on value from AI in this thesis have three contributions to research. First, this thesis contributes to broadening the understanding of value in two ways. By presenting a multi-faceted conceptualization of value, this thesis extends the applicability of the ISBV framework (Schryen, 2013) to different types of organizational value and contributes to a richer understanding of the meaning of AI project success (McLeod et al., 2012). Second, this thesis highlighted the dynamic nature of organizational value generation from AI. Previous research has noted that IT systems must be implemented, or assimilated, into organizations for them to generate value (Roberts *et al.*, 2023). By highlighting the role of practices specific to AI project management in generating organizational value from AI over the lifecycle of an AI initiative, this thesis demonstrates that value generation and destruction are dynamic processes that evolve throughout an initiative's lifecycle. Third, this thesis contributes to research on managing AI initiatives by highlighting the potential of AI to destroy value. Most empirical research on AI development and implementation, including the cases included in this thesis, report on successes.

By elucidating ways in which AI can destroy value, this thesis questions the dominant paradigm in IS research that emphasizes success stories. The cases of value destruction included in Essay 3, and the theoretical propositions of how GenAI could destroy religious value presented in Essay 1 provide specific directions for future research on value destruction by AI.

This thesis has three main implications for practice regarding value generation from AI. First, taking into consideration the multi-faceted conceptualization of value from AI highlighted in this thesis, practitioners should consider the different ways AI might add value and the different types of value that could be generated through AI in when embarking on an AI project. Second, because AI has the potential to generate value for multiple stakeholders, practitioners should consider the different groups who may benefit from an AI project. Third, as this thesis demonstrated that AI initiatives have the potential to destroy value for organizations and other stakeholders, practitioners should carefully evaluate the potential for negative outcomes for all stakeholders prior to commencing an AI project and mitigate these negative consequences accordingly.

Future Directions for Research

Overall, this thesis offers several promising directions for future research. Regarding the broader conceptualization of value from AI, future research should continue to consider the different ways AI can generate value for organizations and the different types of value that can be generated by AI. This research should leverage different conceptualizations of value and explore different measures of value for organizations implementing AI. Longitudinal studies of cases where AI was implemented may offer insights into the long-term implications of AI systems for organizations, employees and other stakeholders. These studies should also explore the long-term implications of AI for organizational value. They should also examine how and in what contexts value destruction from AI unfolds, what type of value can be destroyed through AI, and if and how organizational context influences the value destruction potential of AI. This research would help to better understand how organizations can prevent or mitigate value destruction from AI. Future research could also explore if and how organizations recover after value destruction from AI.

Finally, AI itself is constantly evolving, fueled by advances in technological approaches and methodologies for developing AI systems, coupled with experimentation and exploration of applications of AI, meaning that ongoing research is required to follow the evolution of AI. This thesis proposed several underlying characteristics of AI. While these underlying characteristics of AI may remain over time, as the systems themselves evolve the relevant characteristics may also evolve. For instance, the AI systems presented in Essays 2 and 3 of this thesis were primarily analytical systems. However, current AI systems increasingly use Generative AI (Davenport *et al.*, 2024). In addition, many organizations are exploring commercial applications of Agentic AI (Murugesan, 2025). Additional characteristics may define these systems, and the impact of these characteristics should be studied. In addition, more empirical research is required to understand what patterns enable value creation and what might hinder value creation as organizations adopt these types of AI. Similarly, software development approaches are changing rapidly, with the emergence of low-code and no-code platforms (van Giffen et Ludwig, 2023) and so-called “vibe coding” approaches (Gadde, 2025). These new paradigms are being applied in AI development, potentially challenging extant research in this area as well. Future research should focus on understanding how development teams adapt to these new platforms and approaches, and the implications of the use of these platforms and approaches for value generation.

This thesis demonstrates that organizational value creation from AI depends on more than the technology itself. Rather, it requires the dynamic configuration of organizational elements, AI components, and human practices. By viewing AI as both a technological and sociotechnical system, and by recognizing the multifaceted nature of value, organizations can better navigate challenges, mitigate risks, and strategically align AI initiatives to maximize benefits. Ultimately, organizations gain value from AI through deliberate integration, careful governance, and continuous adaptation to evolving technological and organizational contexts.

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Appendix

Appendices A-F are referenced in Essay 2

Appendices G-Q are referenced in Essay 3

Appendix A : Data structures for stressors, coping resources and coping strategies

Figure A-1 Stressors

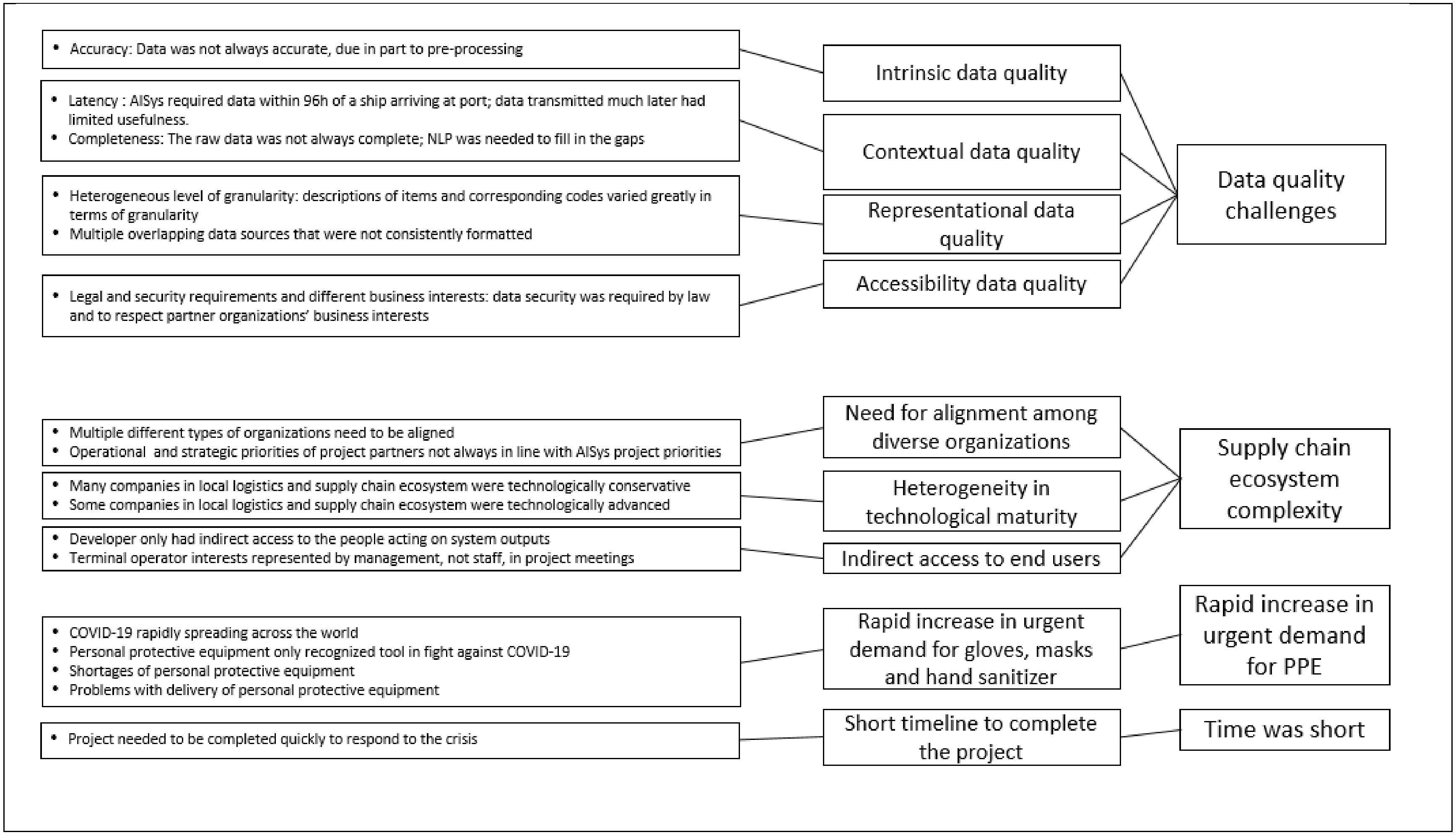


Figure A-2 Coping Resources

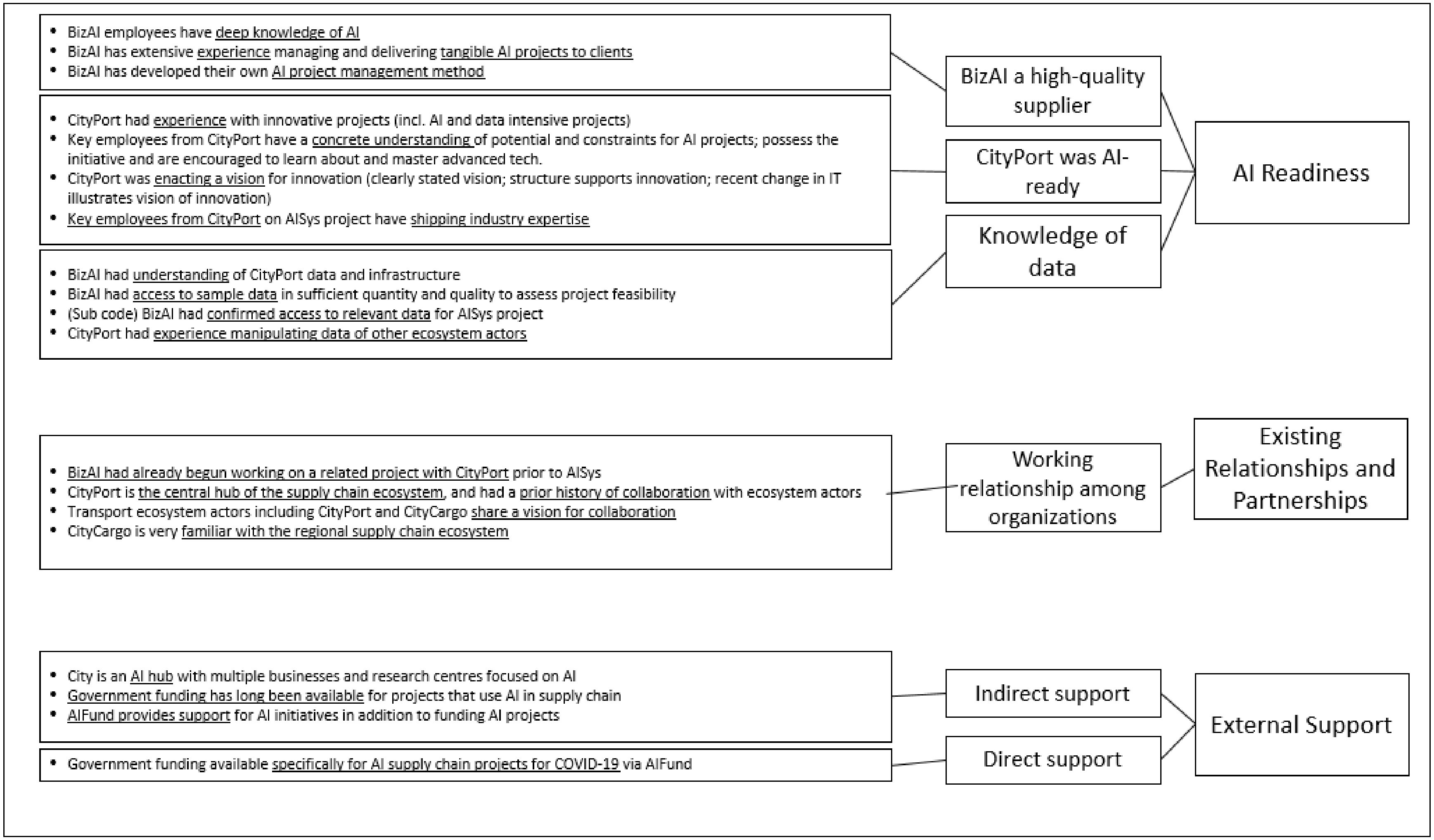
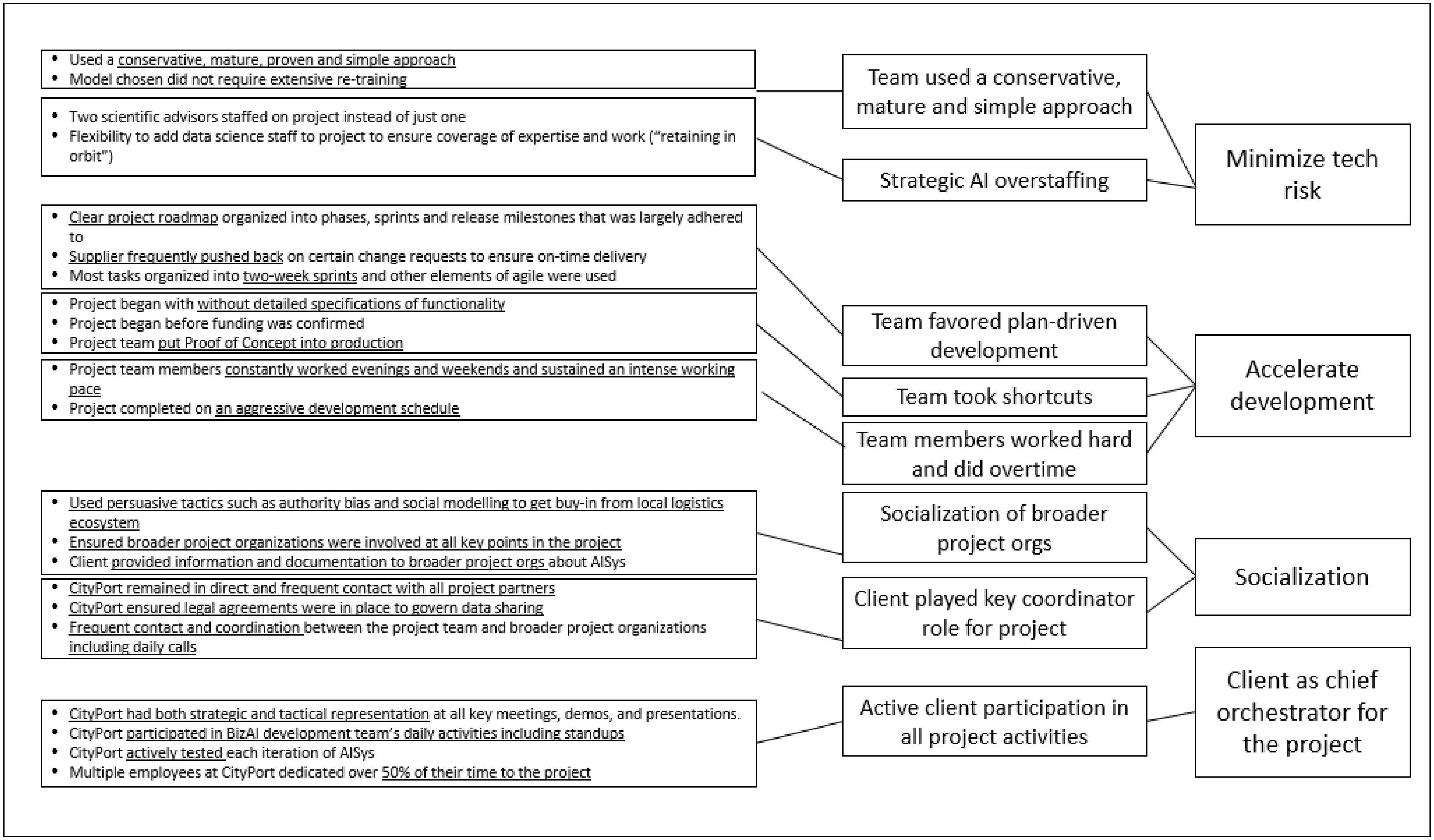


Figure A-3 Coping Strategies



Appendix B: Additional evidence for stressors, appraisal and response

<u>Stressor 1: Rapid increase in urgent demand for PPE</u>

Table B-1 Appraisal and response to the stressor Rapid increase in urgent demand for PPE

Stage	Details	Evidence
Primary Appraisal	The *rapid increase in urgent demand for PPE* was appraised as a **communal opportunity** for the team (as a group) to save lives.	Opportunity to act communally: "*The social aspect of the project, the <u>ability to possibly save lives</u>, was important to <u>all of us</u>"* (Director of IT, CityPort)
Secondary appraisal considering resources	**Low control** over timing **High control** over ability to propose a project. **Resources**: - BizAI had awareness of the existence of a relevant data source. - Project team had access to external funding. - CityPort had experience with AI projects.	<u>Awareness of existence of relevant data source:</u> *"The [cargo manifests] had been evaluated during the blueprint phase [of the ground operations optimize project] so it was a data source that was already known. <u>It was the key, the reason that we [had the go-ahead] because we knew and understood that data source</u>"* (Senior Developer 1, BizAI). <u>External funding:</u> In March 2020, a federal funding agency made grants available for projects that used AI to address supply chain issues caused by the COVID-19 pandemic. <u>Experience with AI projects:</u> "*The other thing that helped a lot is <u>that CityPort, had already realized projects in</u> AI. We were quite realistic about the expectations about an AI solution being developed so fast. That really helped us have a common vision*" (Director of Innovation CityPort).
Coping response	**Accelerate development:** - Team began project before confirmation of funding. - Team proposed an aggressive development schedule.	<u>Accelerate development:</u> The team began developing the system prior to knowing that funding was confirmed for the project (quote in main text: *"We began coding before we knew that the project would be signed [and funding confirmed] because we knew that we had a short timeline, we needed to start right away."* (Senior Developer 1, BizAI)). The project team planned to complete and deliver the system within 12 weeks, which was considered ambitious (see Stressor 2).

Stressor 2: Short time to complete project

Table B-2 Appraisal and response to the stressor Short time to complete the project

Stage	Details	Evidence
Primary appraisal	The short timeline to complete the project was appraised as a **threat**.	The project team felt that completing the project within 12 weeks was ambitious and a source of stress for the whole team (quotes in main text: "*The challenge was the timeline, I'll be honest, it was aggressive*" (Director of IT at CityPort); "*There was a short amount of time to do everything and that of course was not easy*." (Data Scientist from BizAI)).
Secondary appraisal considering resources	**High control** over project management method **Resource:** High quality supplier	<u>High quality supplier:</u> The project management method developed and practiced by BizAI, and the AI expertise of the scientific advisors, helped the project team make staffing and development choices and manage their time during the project (from additional interviews conducted at BizAI). Biz AI had experience successfully delivering AI projects, demonstrating that their approach could work (from additional interviews conducted at BizAI and BizAI website).
Coping response	**Minimize technical risk** - Conservative, mature approach - Strategic AI overstaffing **Accelerate development** - Hard work and overtime - Favoring plan-driven development over agile approaches - Team took shortcuts	**Minimize technical risk:** <u>Strategic AI overstaffing:</u> BizAI staffed two scientific advisors to this project, when normally there is just one. Additional data engineers and data scientists were "retained in the orbit" of the project, available to assist with the project when needed (quote in main text: "*We would try to have people orbit around the project, for example, people who already had access [to the client's infrastructure and data], who already knew the use case, without formally being on the project, just in case. We had some people who came on from outside the project to conduct data analysis for two or three weeks, just to lend a hand. This was unusual for us; it was really unique to this project*." (Technical team lead, BizAI)). <u>Conservative, mature approach:</u> The team decided to use a mature, proven algorithm rather than attempt marginal gains in performance by using more recent techniques (quote in main text: "*With respect to the science, we knew that the science and the basic models were extremely simple, known for around 25 years, so ... obviously, it was not cutting-edge research, but rather techniques that have been proven, and we knew we could move ahead with those techniques, so that considerably de-risked the scientific aspect of the project.* (Senior Developer 1, BizAI)). **Accelerate development:**

		<u>Hard work and overtime:</u> Several respondents from BizAI and CityPort mentioned working long hours and weekends throughout the project: *"Honestly, we worked extremely hard, each one of us. It wasn't rare that we finished working around midnight, each of us at home obviously, … and it wasn't the company that told us to, it was that we were motivated internally, it was an extremely motivating project"* (Senior Developer 1, BizAI) <u>Favoring plan-driven development:</u> The team used an approach that combined aspects of both waterfall and agile development methods but favored waterfall approaches more than usual: "*We had a very precise planning for the project*" (Project Manager, CityPort) "*I'd like to think that the 'waterfall' was even more important for a project that was only 12 weeks*" (Technical Team Lead, BizAI) Project documentation indicated precise timelines for each aspect of the project.

<u>Stressor 3a: Intrinsic data quality</u>

Table B-3 Appraisal and response to the stressor Intrinsic Data Quality

Stage	Details	Evidence
Primary appraisal	Problems with data accuracy (part of *intrinsic data quality*) was appraised as a **threat** by the project team.	Data was not always accurate. This was due in part to preprocessing by CityPort, but also by the wrong data sometimes being transmitted: *"[Sometimes] we get export information but it should be import information, we are not interested in what priority cargo is leaving the country, what interests us is what is arriving. When the wrong information is communicated that can cause problems"* (Senior Developer 1, BizAI) In addition, the data was poorly entered into the cargo manifests (shipping companies may have not used the correct codes or otherwise incorrectly identified items in a container): *"You would often have very vague descriptions, or very messy, or spelling mistakes, things like that, that made it very challenging in some cases to find that needle in a haystack when you're looking for example for ventilators. So that was one of the main challenges that impacted the data science side of things, it was simply trying to work around those data quality issues, with the main field we were working with which was handwritten descriptions of items"* (Data Scientist, BizAI) *"Our two terminal operators…needed to give us a lot of information about the transmission of the data…we had a lot of …corrections to make to the data"* (Project Manager, CityPort)
Secondary appraisal considering resources	**Medium control** over response possibilities **Resource**: Knowledge and understanding of data High quality supplier Existing relationships	Existing relationships with shipping companies allowed the AISys team contact with these companies to address data quality issues: *"I think that the relationship that CityPort has with the big stakeholders…with the terminals, the rail companies and the shipping lines, there was already this vision of collaboration"* (General Manager, LogistiCluster) <u>High quality supplier:</u> The NLP methods used by BizAI were able to compensate for some inaccuracies in the data: *"We need good data for AI. Sure, our NLP methods can correct some of the gaps, and reveal some of the gaps in the data"* (Product Manager, BizAI) <u>Knowledge and understanding of data:</u> "*The blueprint [data assessment phase for the related project] allowed us to conduct a data assessment … we received samples of data with which we could build a wireframe of the solution*" (Senior Developer 1, BizAI).

Response	**Minimize tech risk** Conservative, mature approach **Socialization**	<u>Socialization</u> The AISys team approached shipping companies to educate them on the importance of properly completing cargo manifests and the impact of clear, accurate data on the performance of the system, and on the ability to fast track these items. They also provided information and documentation explaining how to properly identify critical items in cargo manifests: "*What we wanted to socialize, was what you need to do, that [items] must be correctly labeled. Your material has to be well labeled, described with the right codes, and here is the list of codes and what you need to do. It was a standard approach that was fair for everyone, and in addition, it can improve the data, and we need good data to do AI, our NLP methods will fill some gaps but partners need to provide this data so the tool can process it.*" (Product Manager, BizAI) <u>Minimize technical risk</u> BizAI proposed using a conservative, mature algorithm instead of trying cutting-edge techniques that may have higher accuracy but were less consistent in performance.

Stressor 3b: Contextual data quality

Table B-4 Appraisal and response to the stressor Contextual Data Quality

Stage	**Details**	**Evidence**
Primary appraisal	Problems with latency and completeness of data (part of *contextual data quality*) were appraised as a **threat**.	In the early weeks of the project, data was often transferred to CityPort too late, i.e., after a ship had already docked: *"We had some issues with the data…that often arrived too late"* (Senior Developer 1, BizAI) Cargo manifests were often not complete: *"Data completeness, the exhaustiveness, was often an issue"* (Product Manager, BizAI)
Secondary appraisal considering resources	**Medium control** over latency **Resource:** Existing relationships with project partners **Medium control** over response to completeness of data **Resource:** High quality supplier	**Evidence of control over latency** The shipping companies were responsible for transferring the manifests to CityPort, and CityPort had a good relationship with several major shipping companies: *"CityPort and CityCargo were central actors in the ecosystem, they had relationships[with other actors in the ecosystem]…and from this existing relationship, we pushed the project mission of sharing even further"* (Product Manager, BizAI) **Evidence of control over response to low amount of data and completeness of data** The NLP method used by BizAI could compensate for some but not all missing data (See above).
Response	**Socializatiom** **Acceptance**	<u>Socialization</u> CityPort contacted two shipping companies to ask them to change their behaviour and send data sooner, which they did, addressing latency: "*We asked [the shipping lines], 'Can you send [the manifests] a bit earlier? That will really help us identify containers in advance, we will be able to speed everything up.' And two shipping lines changed their process, and we received the [manifests] six or seven days in advance in some cases, compared to 24 hours late before*." (Project Manager, CityPort) <u>Acceptance</u> The NLP algorithm could compensate for some incomplete data The BizAI team clearly informed the client (CityPort) that for around 15% of the cargo, the descriptions were not available and could not be interpreted using other information. This meant that at least 15% of incoming cargo could not be analyzed (from project documentation).

Stressor 3c: Data accessibility quality

Table B-5 Appraisal and response to the stressor Data Accessibility Quality

Stage	Details	Evidence
Primary appraisal	Challenges with the accessibility of data (*data accessibility quality*) was appraised as a **threat**.	Legal and security requirements, as well as business interests, limited data accessibility: *"[CityPort] has rules made by [the government agency that controls it]…on which confidentiality of information, regardless of the nature of the information, is extremely important in all our business processes"* (Director of Innovation, CityPort) *"When we work with a privileged data source like this there are rules, and we have to follow them. There could be industrial espionage"* (Senior Developer, BizAI)
Secondary appraisal considering resources	**Medium control** over accessibility, **Resource**: existing relationships.	CityPort had experience handling and processing data of ecosystem partners over the years and had gained their trust: "*We had good data governance, and a good relationship with our partners*" (Director of Innovation, CityPort)
Response	**Socialization** **Acceptance**	Socialization For freight forwarders and importers, the FAQ on the CityPort website included high-level instructions of how to identify merchandise in shipping and customs documentation so that it could be recognized as critical and benefit from fast tracking, and reassurances that no information describing the contents of a container would be available to transportation organizations beyond the label "priority" (from AISys FAQ on CityPort website). Legal agreements were put in place to govern data sharing for the project. "*[It was important] to target the problematic issue, to circumscribe it, and to put legal agreements in place to govern it [data sharing], which was really well done by CityPort*." (General Manager, LogistiCluster) (Confirmed in project documentation) Acceptance As mentioned above, because of missing data, about 15% of containers could not be identified by the system.

Stressor 3d: Representational data quality

Table B-6 Appraisal and response to the stressor Representational Data Quality

Stage	Details	Evidence
Primary appraisal	Problems with *representational data quality* were appraised as a **threat**.	Level of granularity of descriptions of items in cargo manifests and their corresponding codes varied greatly: *"The other thing that was a challenge, if I come back to this list of 90 [priority items provided by the government], the technical side needs to understand that this list isn't uniform. In the baseline of items we were looking for, there could be items at a very high level, like alcohol, or a chemical product that was extremely precise with a quantity in mL, like 10 mL of X, so we had items at various levels of granularity, and we had to determine how to prioritize them."* (Product Manager, BizAI). Data came from multiple sources that were not always consistent. *"Truly, it was one of the most complex aspects of the project internally…each actor [shipping lines, terminal operators, and ground transporters] has a part of the information and the complete equation gives us the information we need for AISys"* (Director of IT, CityPort) (This was also confirmed in project documentation)
Secondary appraisal considering resources	**Low control** over representational quality	Item descriptions and corresponding codes come from an international system over which the project team had no control (from project and external documentation).
Response	**Satisficing**	The BizAI team did their best with combining data from multiple sources and addressing the level of granularity, but they determined and communicated to internal and external stakeholders that their goal was not perfection or 100% accuracy (from project documentation).

Stressor 4a: Need for alignment among diverse organizations

Table B-7 Appraisal and response to the stressor Need for alignment among diverse organizations

Stage	Details	Evidence
Primary appraisal	The *diversity of types of organizations* for the project was appraised as a **threat**, as was the diversity in operational priorities.	**Evidence of diversity of types of organizations** The project directly involved about 15 different organizations, and impacted many more, who needed to be aligned. The need to align such a diversity of actors was mentioned by several respondents as being a challenge for the project: *"Six shipping lines, customs makes seven, we spoke with two terminal operators so that makes nine, plus LogistiCluster which makes ten, and I'm not even counting the trucking companies…I would say at least 15 companies [were involved]"* (Product Manager, BizAI). (Confirmed in documentation) **Evidence of diversity of organizational priorities** One terminal operator was undergoing a website migration at the time of AISys; rail operations and schedules dictated when a train would depart, regardless of the presence of critical cargo (from interviews).: *"We had some delays, for example, one of our terminal operators was in the middle of redoing their entire website…they were supposed to be responsible for generating notifications [in AISys] which delayed the entire project"* (Director of Innovation, CityPort) *"The issue [for the Terminal operators] was not at all resistance, it was availability. Having time to put in place the mechanisms of prioritization, the tags, etc., was in conflict with the issues they already had."* (Project Manager, CityPort). *"And often, it's the part that is a bit more sensitive, that the terminal operators don't get additional profit or revenue [from AISys]"* (Director of Innovation, CityPort)
Secondary appraisal considering resources	**Medium control** over core project organizations' participation in the project. **Resource:** CityPort had existing relationships and partnerships that could be leveraged. **Low control** over operational priorities of core project organizations	**Evidence of medium control over participation of core project organizations** The existence of LogistiCluster: a developed, established network of supply chain actors, of which CityPort was a member, giving them access to this network: "*We think that the involvement of LogistiCluster, having this cluster in place since 2013, having these players, including the trucking community, present, it was a success factor for this projec*t." (General Manager, LogistiCluster) **Evidence of low control over their operational priorities**

		The project team could not change the priorities and practices of other organizations in the short term; all they could do was leverage existing relationships to communicate importance of AISys and hope it was sufficient to influence behaviour of broader project organizations.
Response	**Client (CityPort) as chief orchestrator** **Satisficing**	<u>Client (CityPort) as chief orchestrator</u> The project team thought carefully about how and when to approach organizations in the local supply chain ecosystem, what messages to share and how to share them. They used different tactics, including producing an informative video about the project, and communicating directly with different levels of hierarchy within other organizations. *"We started by defining the strategy, how we would approach the top management at our partners to engage the entire enterprise, and then how we planned to engage people at an operational level so the daily work can be beneficial and contribute to the velocity of the project, and then how we would obtain feedback from them. It's something we asked ourselves throughout the project."* (Project Manager, CityPort) *"Often you need to motivate them [the terminal operators], have influence, you have to be creative with influence and persuasion, say 'this is a humanitarian project, it's important' even if they are not making money out of it"* (Director of Innovation, CityPort) <u>Satisficing</u> The client and supplier in this case needed to accept that in the project's short time frame they couldn't change the behaviour of other organizations but could only hope for the best. *"We don't want to put too much pressure on our partners' techniques so they don't look bad…we didn't want to 'shorten the leash'"* (Project Manager, CityPort)

<u>Stressor 4b: Heterogeneity in technological maturity</u>

Table B-8 Appraisal and Response to the stressor Heterogeneity in technological maturity

Stage	Details	Evidence
Primary appraisal	The *heterogeneity in technological maturity of the actors in the local supply chain ecosystem* was appraised as a **threat**.	Some companies used sophisticated technologies, whereas some of the trucking companies in the local supply chain ecosystem still operated using fax machines. The project team was not sure companies with limited use of IT would accept and adopt AISys. *"In the context of AI, a port is very conservative, we are not necessarily up to speed technologically speaking…it's a challenge to share new knowledge with our employees"* (Project Manager, CityPort). *"There were trucking companies that still used fax, so sometimes innovation was just not there"* (General Manager, LogistiCluster).
Secondary appraisal considering resources	**Medium control** over core project organizations, **Resource:** existing relationships	While the project team could not change the technological maturity level of organizations within their ecosystem, they could educate and support them, using the socialization strategies described below.
Response	**Socialization**	<u>Socialization</u> As mentioned above, one purpose of socialization efforts was to explain and demystify the project. This was particularly important for actors with lower levels of technological maturity. The informative video, documentation, and website were all used for socialization. In addition, the Project Manager at CityPort educated himself on AI to better be able to explain it to the project partners: "*You have to learn by yourself very quickly, and find answers because the partners we work with often don't have the time to concentrate full time on these things [learning about AI], so that's the role of the project manager, to keep the boat on course, and you have to do everything in your power to get there, so you have to research, understand new concepts*" (Project Manager, CityPort)

Stressor 4c: Indirect access to end users

Table B-9 Appraisal and response to the stressor Indirect access to end users

Stage	Details	Evidence
Primary appraisal	The fact that the supplier only had *indirect access to the people acting on the system output*, via multiple network nodes, was appraised as a **threat**.	The development team did not have direct access to the longshore workers responsible for unloading ships and stacking containers in a way that would optimize the retrieval of critical cargo. This meant they could not predict their reaction to or adoption of the output of the system. *"We had the impression that if we had spoken to the operators, we could maybe have better understood what real levers they had to encourage the COVID containers to leave the port."* (Technical Team Lead, BizAI) *"Anticipating their [the end user's] needs, that's something that is very very difficult."* (Project Manager, CityPort)
Secondary appraisal considering resources	**Low control**	For various reasons the supplier could not have direct access and was not able to negotiate it. *"We had the impression that if we had spoken to the operators, we could maybe have better understood what the real levers they had to encourage the COVID containers to leave the port. Because in reality, other than giving them the information in a little file, we didn't know what else we could do. That was a major issue, particularly with the terminal operators*." (Technical Team Lead, BizAI)
Response	**Workarounds**	<u>Workarounds:</u> Instead of directly with the longshore workers, the project team worked with other adjacent actors. *"We didn't really speak with the longshore workers…we didn't have a direct link with the impact [of the AISys project] on the floor"* (Technical Team Lead, BizAI)

Appendix C: Detailed findings for project outcomes

To ensure that AISys could indeed provide insight into how to successfully manage the complexity of a rapid AI project in a complex supply chain ecosystem, we first examined the project outcomes. The analysis revealed that while process and product outcomes were both positive and negative, there were clear business and strategic gains for the client and the supplier, and even for the ecosystem in general.

Process outcomes

Process outcomes evaluate project management metrics, including time, budget and whether the product was delivered to specifications. According to both the client and the supplier, the project had mixed process outcomes. A working version of AISys was delivered to the client on time: *"It worked"* (Senior Developer 1, BizAI). The client respected the budget, and the few cost overruns were absorbed by the supplier: *"We respected the budget, we respected the timelines"* (Director of Innovation, CityPort). The algorithm could produce a list of containers carrying critical cargo: *"We detected containers with viable merchandise"* (Senior Developer 1, BizAI). However, the system was buggy, and required considerable maintenance, making it less than 100% reliable: *"At the same time there were a lot of missing pieces at the end … a lot of rough edges that were left and also bugs that were remaining"* (Data Scientist, BizAI), and incurring technical debt: *"We ended up paying for these risks [of taking shortcuts] in terms of technical debt"* (Technical Team Lead, BizAI).

Product outcomes

Product outcomes evaluate client satisfaction, including whether the product was used, whether it conferred benefits to the client and if the client was satisfied (McLeod, Doolin et MacDonell, 2012). The innovation team at CityPort used the system regularly: *"I think it was a success because at the end of the day, the client used it [AISys]"* (Technical Team Lead, BizAI); *"[16 months after the system was delivered, AISys] is used every day by the client"* (Senior Developer 1, BizAI). The system was able to identify critical containers with a high level of accuracy: *"It was a great success that it detected the correct merchandise with a success rate that was rather incredible"* (Senior Developer 1, BizAI). Project documentation indicated that the baseline of the algorithmic solution went from a 72% accuracy rate at the beginning of the project to an accuracy rate of 88% at the end. According to CityPort documentation, by January 2023 AISys had identified over 9300 containers. External documentation about the project indicated that dwell time of critical containers could be reduced by up to 50% by using AISys in practice. However, the extent to which

AISys could reduce dwell time was inconsistent because dwell time was affected by other factors over which the project team did not have control: *"We were not able to reduce the dwell time of containers as quickly as we would have liked, so there were containers that remained on the ground too long, even if they were on our radar, for reasons that were completely out of our control*" (Director of Innovation, CityPort). For example, limitations on space which impacted how containers were stacked within CityPort, which affected the ease of retrieving critical containers for delivery.

Organizational outcomes

Organizational outcomes assess the extent to which the product responded to organizational objectives and to what extent they conferred strategic or business objectives (McLeod *et al.*, 2012). Both the client and the supplier noted significant organizational benefits. External and internal documentation demonstrated that the project received several awards and international recognition which benefited both CityPort and BizAI. The project also inspired several other ports in North America to embark on AI projects themselves, as noted by the Product Manager at BizAI: *"And now for example [another North American port] tried to do the same thing, after CityPort. Ports watch each other."*

At the time of the AISys project, CityPort was undergoing various digitalization initiatives. The completion and implementation of AISys accelerated these digitalization efforts. As a concrete example of an AI project, AISys legitimized other AI efforts at CityPort. As a result of the project, there was increased attention on data management, governance, and security at CityPort. Furthermore, AISys prompted an organization-wide improvement in understanding of port operations at CityPort, which positively impacted relations between departments and organizations, as described by the Project Manager at CityPort: "*It allowed some of the layers of executives to better understand the operational realities [of the port] and the realities of the pandemic.*" The AISys project received considerable positive media attention: several articles were published in local and international outlets about the project. This had a positive impact on the credibility and reputation of CityPort, as noted by the Director of Innovation: "*Our president at the time … was a member of a federal committee on managing the pandemic, and [the AISys] project really gave enormous credibility to CityPort in its effort to fight the pandemic and gave us international renown.*"

BizAI gained renown through the AISys project. The media attention and awards the project received also allowed BizAI to gain visibility. AISys became a star project that BizAI could showcase to future clients, as noted by the Product Manager at BizAI: "*The CEO, who began in early 2021, said that AISys was the project of the year … that it attracted an enormous amount of attention for other clients*."

AISys stood apart from many other AI supply chain projects at the time. According to documentation from AIFund, over 160 projects were submitted to AIFund requesting funding for AI supply chain projects in March 2020, eight of which received funding. Not all the eight projects succeeded, and no other project received as much positive media attention as AISys.

Supply chain ecosystem outcomes

The benefits of AISys extended beyond the client and the supplier. The introduction of a working AI application in the supply chain ecosystem prompted an increased awareness and interest in AI in the ecosystem, as the General manager from LogistiCluster noted:

> *AISys democratized the use of data [for the sector], and particularly in this sector over the past few years … People didn't know what [AI] was, it was a buzzword … researchers worked on it. Now they have seen it concretely, we use it. At the end of the day, it's a red flag on a line on your distribution sheet, but behind that there was a lot of work, a lot of data to bring that red flag, [and now] they see it. For me it is an enormous success to have brought the community to realize what data usage is, what artificial intelligence is, and to bring people to use it.*

This increased interest was sustained: in the spring of 2023, almost three years after the launch of AISys, LogistiCluster hosted a webinar for their members about AI in supply chain which was attended by over 50 participants. This increased interest translated into an improvement in data management and inter-organizational data transfer, as the Director of Innovation at CityPort explained:

> *Yes, we have seen clearly [since the beginning of the AISys project] that there has been an improvement in the discipline of data transfer … and I think it's permanent. In any case, we will make sure it stays because [AISys] is a project that aims to conduct predictive analysis. The further in advance we can obtain the data, the better the algorithm will perform. We have every interest in keeping this discipline in place.*

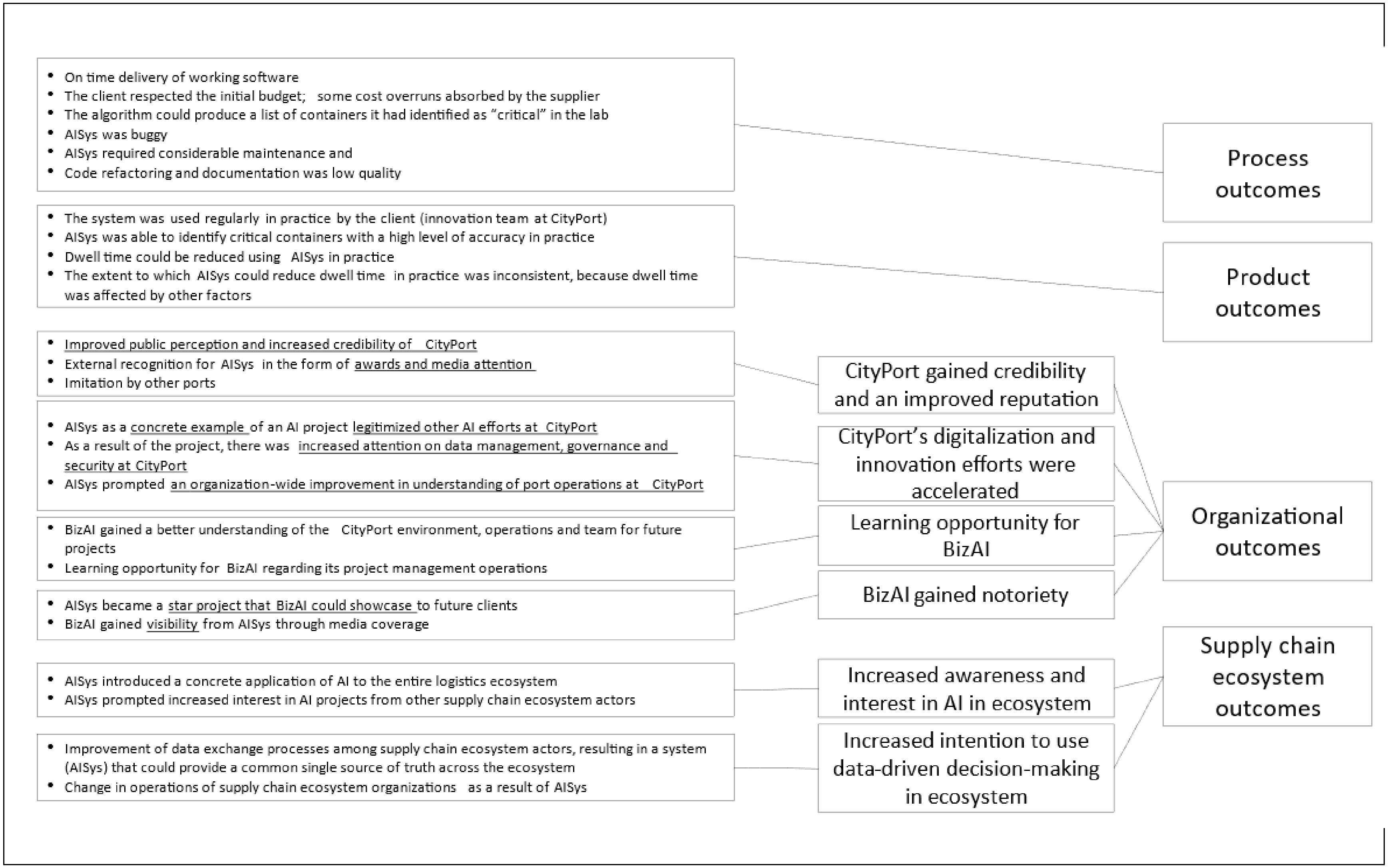


Figure C-1 Project Outcomes

Appendix D: Semi-Structured Interview Guide

All interviews were semi-structured, and the questions presented here served as prompts. When appropriate, respondents were asked to provide additional details. These questions were used in the initial round of interviews. The second round of interviews focused on clarifications and specifications. For reasons of confidentiality, the questions used in the second round of interviews are not included here.

Part 1: Introduction and overview:

GOAL: Understand the person and their role (overall and daily tasks)

1. Respondent introduction
    a. Please provide your name, the organization you work for, your position, and your role on the AISys project
    b. Please briefly describe your education and work experience prior to your current role.
2. Project
    a. Please provide a brief description of the project from your perspective or based on your participation in the project

These next questions were asked where relevant based on the respondent's organization and role on the project.

    b. Please describe the project governance structure.
    c. What was the project timeline? How was it established and followed?
    d. How was progress tracked? For example, what milestones were set?
    e. What types of data sources were necessary to this project? How was data prepared?
    f. How was the system integrated into your organization's operations?
3. Role on project
    a. At what point did your organization get involved in the project?
    b. What was your organization's role on the project?
    c. At what point did your involvement in the project begin?
    d. On a daily basis, what was your role and what were your responsibilities on the project?
    e. Who else was involved in the project from your organization? Was the team consistent?

Part 2: Overall assessment

GOAL: understand if this respondent thinks the project was a success, why or why not, and how they qualify it as a success

1. What is your overall evaluation of the project?
    a. What was the impact of this project on your organization?
    b. Was the project a success?

   c. How do you define the success of this project?
   d. Is the system still in use?
   e. Who are the system users? How do they use the system?

Part 3: What worked, what went well?

GOAL: Understand if there was anything the project team was able to get right early on.

1. What were two or three things that went particularly well on the project, from the beginning or close to the beginning? Describe specific incidents or events to illustrate.
   a. How did these successes relate to AI/ML?
2. How did these successes impact the project?

Part 4: What was difficult?

GOAL: Understand the different factors that hindered the project.

1. For you, what were the two or three main obstacles in this project? Describe two or three incidents or events. These can be in relation to the project management or the technical aspects of the project.
   a. Why were these events challenging?
   b. How did these challenges relate to AI/ML?
2. Were you able to overcome these challenges?
   a. If so, how? Please provide details or examples
   b. If not, why not?
3. How did the pandemic related urgency contribute to the project?

Part 5: Comparison with other projects

GOAL: Understand what is specific to AI, and how the specifics of AI contributed to the challenges of the project.

1. What were the main differences you noted between this project and other projects that you have participated on, that did not involve AI?
   a. Were there differences in project governance?
   b. Were there differences in how the project was managed? (Probe based on the 10 project management knowledge areas)
   c. Were there differences in client involvement? What was the nature of these differences?
   d. Was this project more, or less, challenging than other projects you worked on? Why do you think that is?
   e. What were the similarities between this project and others you have worked on?

Part 6: Closing

GOAL: Wrap up the interview, provide opportunity to add anything.

1. [Where relevant] What is next for this project? What challenges do you anticipate for the next steps?
2. Please share one or two key insights or learnings about AI/ML that you acquired during this project that you could apply in future projects.
3. Is there anything else about the project that you would like to add?

Appendix E: Literature Review of Project Management Practices

The following is a detailed review of the literature reported in the Literature Review section of the paper.

IS Project Management

IS project management is the process of planning, scheduling, executing, monitoring, and reporting on IS projects.

Strategic practices

There are several strategic practices that are recommended. At the outset, the project should be aligned with the business' strategic objectives using a clear business case (Ward, Daniel et Peppard, 2008). Top management should demonstrate their support throughout the project (Esteves *et al.*, 2002; Kloppenborg *et al.*, 2015). Involving stakeholders and developing mutual understanding between them (Barki, Paré et Sicotte, 2008; Jenkin, Chan et Sabherwal, 2019) is also important.

Project practices

IS projects are characterized by frequent changes; therefore, project managers should also expect and welcome change (Conboy, 2009; Williams et Cockburn, 2003). End users should be involved throughout the project to help ensure the system being developed or implemented responds to their needs and will be used (Barki *et al.*, 1994; Barki *et al.*, 2008). Project risk should be assessed and addressed throughout the project (Moeini et Rivard, 2019).

Team/people practices

IS projects are often a team endeavor. Software development teams should be cross-functional and interdisciplinary (Dremel *et al.*, 2017; Lee et Xia, 2010), a recommendation that is core to agile methodologies (Cockburn et Highsmith, 2001; Conboy, 2009). Team autonomy should be encouraged (Moe *et al.*, 2019), as should communication among team members (Hennel et Rosenkranz, 2021). IS projects should have a project champion (Eom *et al.*, 2020; Esteves *et al.*, 2002).

Process practices

In the early days of software development IS projects followed clear and formal plans (Fitzgerald, 1996). Over the past two decades, different iterative approaches have been introduced, such as Scrum or Extreme Programming, and have generally proven to be more effective than planned approaches (Dingsøyr *et al.*, 2012; Standish Group International, 2015). In reality, many teams adopt hybrid approaches that are tailored to their situation or the project (Cram, 2019; Hassani-Alaoui *et al.*, 2020). Often several changes occur during an IS project and therefore a good project management approach can integrate changing requirements (Heikkila *et al.*, 2017; Williams *et al.*, 2003).

AI Project Management

An AI project is defined as "*an undertaking that aims to deliver a working software product or service that embeds AI functionality, to be used by humans or machines toward the accomplishment of an objective*" (Vial *et al.*, 2023 : 670).

Strategic practices

AI projects benefit from a strategic vision for AI (Al Ali et Badi, 2021; Scheepers *et al.*, 2018). Organizations should possess AI resources, AI skills and expertise, and AI intangibles (Chang, 2023; Janssen *et al.*, 2022; Lee *et al.*, 2023; Lou *et al.*, 2021). They should take a stakeholder first approach (Bell *et al.*, 2023), which involves understanding the needs and concerns of stakeholders at all levels, from top management through to end users, present the benefits to address their concerns (Campion *et al.*, 2022). AI projects often involve organizational change, which must be managed (Lee *et al.*, 2023). It helps to anticipate unintended effects of AI (Asatiani *et al.*, 2021; Asatiani *et al.*, 2020). Finally, ethical issues of AI projects, including autonomy, explainability and transparency should be addressed (Balasubramaniam *et al.*, 2020).

Project practices

AI projects should begin by determining the data ground truth (Lebovitz *et al.*, 2021; Scheepers *et al.*, 2018). Ensuring data accessibility is also important(Vial *et al.*, 2021). Organizations should adopt conservative approaches (Eckroth, 2020), and should question the marginal value of additional computation that may only bring marginal returns (Vial *et al.*, 2023).

Team/people practices

AI projects benefit from multidisciplinary teams with specific experts, including subject matter experts, data scientists and data engineers (Golovianko *et al.*, 2022; Gronsund *et al.*, 2020; Lebovitz *et al.*, 2021; Reis *et al.*, 2020; Scheepers *et al.*, 2018; Vial *et al.*, 2023). They require project champions and boundary spanners (Campion *et al.*, 2022). Team leadership, specifically an AI power couple that combines both business and technical expertise, brings understanding from two sides (Vial *et al.*, 2023).

Process practices

AI projects involve practices from many different traditions, and therefore the process involves carefully managing conflicts in institutional logics – traditional project management, agile project management and the AI workflow (Vial *et al.*, 2023). Often AI projects are conducted in phases, each release including ever expanding capabilities (Scheepers *et al.*, 2018; Vial *et al.*, 2023). AI development is an iterative process of including and excluding human expertise (Binder *et al.*, 2022; Gronsund *et al.*, 2020; van den Broek *et al.*, 2021). Organizations wishing to implement AI systems need to begin by understanding how the algorithms work and how their output influences organizational processes (Scheepers *et al.*, 2018).

Complex Project Management

Project complexity can be defined as "*an intricate arrangement of the varied interrelated parts in which the elements can change and evolve constantly with an effect on the project objectives*" (Bakhshi, Ireland et Gorod, 2016 : 1203). Complex projects are different from complicated projects and chaotic projects in some important ways. Complicated projects require the coordination of interrelated elements, but with specialized knowledge or expertise, can eventually be predicted and planned. Chaotic projects are completely unpredictable and characterized by a lack of constraints (Bakhshi *et al.*, 2016; Snowden et Boone, 2007). In contrast, complex projects "*consist of ambiguity and uncertainty, interdependency, non-linearity, unique local conditions, autonomy, emergent behaviours and unfixed boundaries*" (Bakhshi *et al.*, 2016 : 1201).

Strategic practices

Complex projects are risky and require rigorous risk management (Lyneis, Cooper et Els, 2001). A systems thinking approach which considers "dynamic, non-linear and multicausal structures and processes" at play within a project helps to capture and understand the complexity of a project (Saynisch, 2010 : 7). Orchestration of project partners, defined as undertaking deliberate actions to set up and manage an inter-organizational network for the purpose of creating and accessing the resources, assets, and capabilities of network members, is beneficial for maintaining the collaboration of project partners, and is particularly beneficial at the project outset (Roerich et al., 2013). Top management needs to frame the problem to be solved, and solutions should address many organizational objectives (Ahern *et al.*, 2014).

Project practices

Complex projects benefit from minimal planning (Ahern *et al.*, 2014; Butler *et al.*, 2020). Successful management of complex projects often features an "emergence of consciousness instead of precise and quantitative plans or duty points" (Saynisch, 2010 : 9).

Team/People practices

Situational awareness, trust, face-to-face communications, and collective intelligence can all positively influence the success of complex projects (Hansen *et al.*, 2020). Leadership should be distributed rather than centralized (Ahern *et al.*, 2014). Cheetah teams – defined as a team of experts brought in to solve a specific complex problem – are often effective in completing complex projects (Engwall et Svensson, 2001). Other recommendations include using targeted staffing approaches to address the specifics of the project as well as targeted development activities for project managers (Lyneis *et al.*, 2001; Maylor, Turner et Murray-Webster, 2013).

Process practices

In complex projects, it helps to understand the sources of complexity and then address sources of complexity using a tailored approach (i.e. specific sources of complexity require different approaches) (Floricel, Michela et Piperca, 2016; Maylor *et al.*, 2013). In general, however, agile approaches seem to be particularly well suited to IS projects that are highly dynamic and complex (Butler *et al.*, 2020). Both hybrid and agile approaches appear to achieve better stakeholder success than traditional approaches (Gemino, Horner Reich et Serrador, 2021). This may be because highly structured approaches to managing a complex project can inadvertently increase the level of complexity of the project (Maylor *et al.*, 2013).

Supply Chain Project Management

A supply chain is a dynamic, complex entity that "*consists of two or more legally separated organizations, being linked by material, information and financial flows*" (Stadtler, Kilger et Meyr, 2015 : 3). Supply chain projects are a type of complex projects and can be defined as “dyadic activities between existing alliance partners that have already established a relationship” (Brinkhoff *et al.*, 2015 : 181). They can range from functional improvements to the information systems within the supply chain to large-scale, transformative projects (Kilger, 2015).

Strategic practices

Like for many types of projects, supply chain projects should be aligned with the company’s strategy (Carlan *et al.*, 2017; Cichosz, Wallenburg et Knemeyer, 2020). A supply chain is a network of actors and therefore collaboration is importantt (Ayers, 2003; Simangunsong, Hendry et Stevenson, 2012). Supply chain projects require top management commitment and championing (Brinkhoff *et al.*, 2015; Carlan *et al.*, 2017; Cichosz *et al.*, 2020). A systems engineering approach to project governance is helpful (Locatelli *et al.*, 2014). Effective inter-organizational information exchange is crucial for supply chain projects (Ryoo *et al.*, 2015).

Project practices

Complex projects benefit from process standardization, integration, and governance (Brinch *et al.*, 2021), but also short-term timelines rather than long-term plans (Ala-Risku et Karkkainen, 2006).

Team/People practices

Employee commitment (Brinkhoff *et al.*, 2015), as well as employee training and skills development (Brinch *et al.*, 2021; Cichosz *et al.*, 2020) are beneficial to supply chain projects.

Process practices

Supply chain projects gain by adopting a structured approach to managing and controlling changes (Ayers, 2003). They rely on collaboration among supply chain actors (Brinkhoff *et al.*, 2015; Simangunsong *et al.*, 2012). Collaboration involves communication, coordination and information sharing, and is the most frequently adopted strategy to mitigate control risk (Shekarian *et al.*, 2021) as both information sharing and collaboration have been demonstrated to have a positive impact on supply chain performance (Wu *et al.*, 2014). Flexibility was demonstrated to be the most used strategy to mitigate most types of supply chain risk, including uncertainties in the external environment (Cichosz *et al.*, 2020; Shekarian *et al.*, 2021).

Urgent Project Management

According to the Merriam-Webster dictionary, urgent is defined as “calling for immediate attention.” Urgent projects therefore need to be completed quickly in response to urgent situations. Successful management of urgent projects relies on many of the same factors applicable to all projects. However, since time is an important metric for these projects, practices specific to the acceleration of urgent projects are particularly salient (Wearne, 2006).

Strategic practices

Urgent projects benefit from top management support (Brown *et al.*, 1995; Wearne, 2006; Wearne *et al.*, 2014). They require a clear goal (Chen, Damanpour et Reilly, 2010). Speed should be prioritized, by making time a goal (Ellwood *et al.*, 2017; Wearne, 2006; Wearne *et al.*, 2014). This often means that there should be less emphasis on the budget (Wearne, 2006; Wearne *et al.*, 2014).

Project practices

In urgent projects, the scope is usually less well defined (Wearne, 2006), and there is less emphasis on planning and control (Lechler et Grace, 2007). Schedule compression is one of the most frequent practices in urgent projects (Wearne *et al.*, 2014). Techniques that can be used to accelerate projects to make up for project delays include activity crashing, defined as adding extra resources to an activity; activity overlapping, defined as beginning an activity before the previous one is complete; and activity substitution, meaning replacing an activity with a different approach, technique or technology (Gerk et Qassim, 2008).

Team/people practices

Some research suggests that collaborative problem solving among stable teams is helpful in urgent projects (Nazir *et al.*, 2022), whereas other studies suggest that cheetah teams – ad-hoc teams with specific expertise – are appropriate for urgent projects (Engwall *et al.*, 2001; Wearne, 2006). Regardless, teams for urgent projects should be cross-functional (Brown *et al.*, 1995) and ideally should be collocated (Ellwood *et al.*, 2017). Regardless of their composition, within teams, there should be early and consistent communication (Wearne, 2006; Wearne *et al.*, 2014). Team leadership should have experience and be dedicated to the project (Chen *et al.*, 2010). One technique is to employ “double-headed leadership,” or including top management from two or three involved project partners (Wearne, 2006).

Process practices

Urgent projects feature short timelines and therefore require built-in flexibility (Conboy, 2009). It is not surprising that iterative development and agile approaches are often used for these projects (Brown *et al.*, 1995; Chen *et al.*, 2010; Conforto *et al.*, 2016).

Fast Response/Crisis Management

Fast response organizations are "organizations where decisions must be made rapidly and where errors can be fatal" (Faraj et Xiao, 2006 : 1155) such as fire stations and medical trauma centres. Crisis management teams "coordinate various prevention, mitigation and response activities – and they are required to operate quickly and appropriately in an ambiguous, risky, and constantly changing environment" (Thielsch *et al.*, 2021 : 151). Since the mission of these organizations is to respond quickly to disaster and not to plan projects in advance, rather than examining specific project practices, the general operations of these organizations are synthesized below.

From a strategic perspective, these organizations should foster situational awareness (Schakel et Wolbers, 2021). Project managers should be vigilant of the project environment to see changes and unexpected events in projects (Söderholm, 2008). From an organizing perspective (similar to project practices), fast response organizations benefit from efficient orchestration (Baham *et al.*, 2017). Both centralized and decentralized approaches to crisis response can be effective(Schakel *et al.*, 2021). Successful fast response organizations often feature established, stable teams with domain expertise (akin to team/people practices) (Baham *et al.*, 2017; Faraj *et al.*, 2006; Kotlarsky, Van Den Hooff et Geerts, 2020; Thielsch *et al.*, 2021), and rely heavily on teamwork (Thielsch *et al.*, 2021). Finally, from a process perspective, fast response organizations focus on coordination (Faraj *et al.*, 2006), flexibility (Schakel *et al.*, 2021) and using tailored agile approaches (Nazir *et al.*, 2022).

Disaster Management

Another stream of literature which is important to understanding urgent projects is disaster, or emergency response. Emergency response groups are formed after a disaster or catastrophic event and are defined as "collectives of individuals who use nonroutine resources and activities to apply to nonroutine domains and tasks, using nonroutine organizational arrangements" (Majchrzak *et al.*, 2007 : 150). Similar to fast response organizations, these organizations operate in response to an urgent and unexpected situation, and a project management lens which focuses on planning is less appropriate. Therefore, general operations of these organizations are also synthesized here.

First, from a strategic perspective, while disasters themselves are unplanned, multi-level governance, specifically in the development of disaster-response information systems, has been found to have an overall positive impact(Maldonado, Maitland et Tapia, 2010). Disaster response organizations are reactive, and communication channels are opportunistic (organizing, or project perspective) (Majchrzak *et al.*, 2007). Team/people practices include the reliance on emergent, interdependent and fluid teams that often lack expertise and training specific to the situation (Majchrzak *et al.*, 2007; Nazir *et al.*, 2022) and these initiatives often feature opportunistic coordination (process perspective) (Majchrzak *et al.*, 2007).

Defining Project Success

As our research question examines how organizations can successfully manage AI projects, and as we are purporting to examine one successful case study, we needed to understand the multifaceted nature of project success. Therefore, project success criteria are also reviewed.

Organizations evaluate project outcomes for many reasons, one of which is to determine whether a project was successful (Bannerman, 2008; Rode, Svejvig et Martinsuo, 2022). Project success is a multidimensional construct (Bannerman et Thorogood, 2012; McLeod *et al.*, 2012). It can be evaluated using a multilevel framework of process outcomes, product outcomes and organizational outcomes (Bannerman, 2008; Bannerman *et al.*, 2012; McLeod *et al.*, 2012).

Measurements of the first dimension, process outcomes, assess project efficiency using the “iron triangle” of project management outcomes: if the project was delivered on time, on budget and to specifications (Nelson et Morris, 2014). For AI projects, the specifications can include target accuracy of an algorithm or other model metrics (Kshirsagar *et al.*, 2021; Mogyorosi *et al.*, 2021; Vial *et al.*, 2023). The opacity of many AI algorithms can make it difficult to evaluate the process of arriving at an answer (Faraj, Pachidi et Sayegh, 2018), therefore limiting the ability to determine if a system responds properly to specification.

The second dimension focuses on product outcomes and assesses client satisfaction outcomes including whether the product was used, if the client was satisfied overall with the project and if the end users benefit from the project (McLeod *et al.*, 2012; Nelson *et al.*, 2014; Zidane et Olsson, 2017). End users may embrace AI systems, or they may find ways to avoid using the system (Strich *et al.*, 2021). End-user satisfaction for AI systems can include an assessment of their speed and accuracy, as AI systems can process data more rapidly and provide more accurate predictions than earlier systems, but also on their impact on the individual user (Reis *et al.*, 2020; Strich *et al.*, 2021).

The third dimension focuses on organizational outcomes and measures organizational objectives such as business benefits and other organizational benefits (Jugdev et Müller, 2005; McLeod *et al.*, 2012; Nelson *et al.*, 2014). AI systems may lead to improved client outcomes and employee work environment (Dicuonzo *et al.*, 2023), or to decreases in employee morale or sense of professional identity (Mayer *et al.*, 2020; Reis *et al.*, 2020; Strich *et al.*, 2021). Successful AI implementations may lead to improved decision-making capability and increased process agility (Borges *et al.*, 2021; Soman *et al.*, 2022).

Some project outcomes can only be measured over time and returns on investment often increase over time. Therefore, success is dependent on the time at which it was measured (Bannerman *et al.*, 2012; McLeod *et al.*, 2012). Furthermore, success in one dimension does not imply success at other dimensions. For example, the product or deliverable could be successful (product outcomes), but the time and budget were not respected (process outcomes). While success in any dimension can generate value for organizations, the highest potential for value creation and capture is when projects achieve strategic success at the organizational level (Bannerman, 2008; McLeod *et al.*, 2012). Organizations are only beginning to implement AI systems at a large scale, and therefore measuring long-term benefits may not yet be possible (Borges *et al.*, 2021).

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Table E- 1 Recommended Practices from Various Project Management Contexts

Type of practice	IS project management	AI project management	Complex project management	Supply chain project management	Urgent project management	Fast response / crisis management organizations	Disaster management
Strategic	• Clear business case • Top management support • Mutual understanding among stakeholders	• Strategic vision for AI • AI resources, AI skills, AI intangibles • Stakeholder first approach • Address ethical issues.	• Systems thinking • Orchestration • Risk management • Top management support • Frame project in line with organizational objectives	• Alignment with company strategy • Collaboration among organizations • Top management commitment • Systems engineering approach.	• Top management support • Prioritize speed • Less emphasis on budget • Goal clarity	• Foster situational awareness	These are initiated in response to a disaster, not thought out in advance, no strategic practices
Project	• Expect and welcome change. • Involve end users. • Address project risk	• Ensure data quality and accessibility. • Use conservative approaches. • Determine need for marginal increases in performance.	• Put minimal emphasis on planning. • Foster “consciousness” instead of quantitative plan	• Focus on process standardization, integration and governance. • Favour short term timelines	• Less well-defined scope • Less emphasis on planning and control • Schedule compression	• Focus on efficient orchestration • Use both centralized and decentralized approaches	• Use opportunistic communication
Team / people	• Teamwork • Colocation • Communication • Encouraging team autonomy • User involvement • Project champion	• Multidisciplinary teams with specific experts • Adding champions and boundary spanners	• Distributed leadership • Targeted staffing to address the specifics of the project • Cheetah teams • Develop situational awareness	• Employee training and skill development • Employee commitment	• Collaborative problem solving • Cheetah teams • Colocation • Cross-functional teams • Double-headed leadership	• Established teams with domain expertise • Teamwork	• Emergent, interdependent and fluid teams
Process	• Choice of approach (between agile, plan-driven or hybrid approaches) depends on project context	• Phased yet iterative approach • Understanding how algorithms work, how their output influences organizational processes	• Tailored approach • Agile and hybrid approaches	• Information sharing • Lean and agile approaches	• Iterative development • Agile approaches	• Coordination • Tailored agile approaches • Flexibility	• Opportunistic coordination

Appendix F: Alternate Theoretical Perspectives Considered and Rejected

Table F- 1 Theories considered and subsequently rejected during initial phase of data analysis

Theory	**Description**	**Reason not retained**
Empathy-altruism hypothesis (Batson *et al.*, 2017; Batson, Lishner et Stocks, 2015)	Empathy, i.e., being able to feel for the other, is what fuels altruism. Altruism is a motivation to do good for others.	Explained the desire to complete the project well and on time, but did not explain how the team was able to address project complexity or project urgency.
Job demands-resource model (Bakker et Demerouti, 2017)	Different aspects of a job are sources of motivation and strain. Both motivation and strain predict job performance.	The Job demands-resource model is used to understand long-term situations and considers job demands and resources as relatively stable factors in the job environment, and not episodic sources of stress nor stress in short term projects.
Challenge-Hindrance Stressors model (Horan *et al.*, 2020)	Stressors are appraised as either a challenge (opportunity) or a hindrance (threat) and their appraisal influences how individuals respond to stress	This theory explains the appraisal of stressors and the relationship between stressors and strain, but does not explain coping resources or coping strategies.

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Appendix G: Coding Form for Meta-Synthesis

Table G-1 Coding Form for Meta-Synthesis

Study information	Reference (citation) – if multiple studies, include citation for all
	Goal – RQ – if multiple studies, include RQ for all
	Goal – stated contribution – if multiple studies, include contribution for all
	Author explanation for outcomes – if multiple studies, include explanation for all
Study context	Context - Geography
	Context - Industry
	Context - Type of system
	Context - Phase(s) of implementation explored in paper
	Context - Motivation to implement system
	Context - Internal or external development
	Context - Focus of article
	Context - Cognitive function being automated/augmented
System description	Ground truth of the system; how it is determined
	Type of model - explainable or not, other details provided in the paper
	Output "binding" or not - how do/can users act on the system output?
Study rigor and validity	Method - Research Design (case study, action research e.g.)
	Method - Sampling strategy
	Method - Use of a case study protocol
	Method - Team-based research
	Theoretical framing (perhaps not relevant for me)
	Data sources/collection - Timing (retrospective vs real time)
	Data sources/collection - Type(s) of data
	Data sources/collection - Data management (e.g. case database)
	Reporting - Data reported (direct quotations, inferences, e.g.)
	Reporting - Chains of evidence (??)
	Reporting - Evidence of pattern matching, explanation building, etc.
Other	Missing information
	Inconsistencies
	Other comments
Data extraction about development and implementation	

Phases described in the study (list)	
System development	Who was involved and how (developers - internal or external, end-users, domain experts)
	Human involvement at the developer
	Human involvement at the client
	Data (type of data, source of data)
	Approach to ensuring data quality
	Changes in data during development
	Changes made during development
	Nature of human involvement in developing the system
	System interface
	Data source
	Nature of data
	Goal/purpose of the system
	Automation/Augmentation
	Type of technology used
System implementation	Who was involved and how (developers, end-users, domain experts, people impacted, change management experts/HR)
	Human involvement at the developer
	Human involvement at the client
	Phases or cycles of implementation
	Changes made during implementation
	User reaction when first introduced to the system
System outcomes/impact	User reactions; outcomes
	How people (not users) were impacted
	System use post-implementation
	Organizational impact
	Success/Failure/Mixed
What contributed to outcomes	Impact for users
	Impact for client organization
	Impact for supplier organizations
	Impact for provider
Impact of	Opacity
	Data-dependency
	Unpredictability
	Autonomy of AI

How they were dealt with	Opacity
	Data-dependency
	Unpredictability
	Autonomy of AI
Evidence of tactics	Phased development
	Dataset curation
	User demos
	Developer openness to user- and domain-driven changes
	AI and data literacy training for non-technical employees
	Knowledge brokers
	Black-boxing the technology
	Multi-disciplinary teams
	Subject matter experts
	Workflow redesigns
	Mandating system use
People involved and when	Top leadership
	Management
	User
	Developer
	Expert
	SME
	Other

Appendix H: Presence and Consequences of Characteristics of AI

Table H-1 Presence and consequences of characteristics of AI

Case	Inscrutability	Learning-Driven Data Dependency	Learning-Driven Unpredictability	Autonomy	Consequences of the Characteristics of AI
1. CAS	High: The algorithm was opaque and not explainable. Even though the parameters were shared, the developers were not willing to try to explain the algorithm to the users, indicating limited transparency. Users struggled to interpret the output. *"However, because the map did not offer any insights into the causes, they had little clue about the meaning of these predictions in the context of the police"* (Waardenburg et al., 2022, p. 68). *"This [the learning nature of the system], in combination with the size of the data set and the high number of predictions, made the*	High: CAS was dependent on data from past crimes for training and required current data to make predictions. *"For the CAS algorithm to learn, the data scientists constructed a data set with historic high-impact crime data"* (Waardenburg et al., 2022, p. 63).	Medium: The system would sometimes make predictions that did not make sense (e.g., suggesting car theft in a place where cars are not allowed). *"In another instance, … one of the intelligence officers emailed the data scientists to share that CAS generated predictions for car burglaries in areas where cars were not permitted"* (Waardenburg et al., 2022, p. 72).	Low: The system autonomously made predictions, but these were first interpreted by intelligence officers, and then police managers could use the predictions to inform the allocation of resources. *"The model was thus able to autonomously learn and generate predictions"* (Waardenburg et al., 2022, p. 64). *"'We give our advice,' intelligence officer Wendy reflected, 'and most of the time the police managers allocate police resources accordingly'"* (Waardenburg et al., 2022, p. 75).	Inability to overcome high inscrutability and unpredictability led intelligence officers to not use the system as intended and instead engage in workarounds. *"In sum, the intelligence officers eventually realized that the boundary between machine learning and their human interpretation of crime predictions was impassable. As a consequence, they pushed back the learning algorithm and substituted it with explainable alternatives that aligned with their human judgments and that they considered most suitable for the police managers"*

	internal decision logic of predictions opaque in practice, even for the data scientists" (Waardenburg et al., 2022, p. 64).				(Waardenburg et al., 2022, p. 75).
2. COMPAS	Low/Medium: The case did not provide information on the algorithm. However, a web search of the COMPAS system found that the algorithm is publicly available, indicating transparency. Explainability, opacity, and interpretability are not possible to assess. *"Interestingly, if the COMPAS model were not proprietary, its documentation [29] indicates that it would actually be an interpretable predictive model. (It is a black box of the second type – proprietary – but not the first type – complicated – discussed above.) Revealing this model, however, would be revealing a trade*	High: Local data was required to adapt the system for the local context. *"I needed to get this process moving, so we entered into the contract with COMPAS…and [tried] it out on our jail population…My program director… did an interview on every person that was in the jail, so we could get a baseline as to what the top criminogenic needs were"* (Hartmann and Wenzelburger, 2021, p. 277).	Not provided.	Low: The system provides a risk score that lawyers and judges can use to inform sentencing. *"Some of them still emphasized the discretion of human actors and the non-binding role the risk scoring by the ADM system played"* (Hartmann and Wenzelburger, 2021, p. 281).	No link or connection was explicitly evident based on evidence from the case.

	secret." (Rudin, 2019, p.8).				
3. Watson	Medium: Watson is a proprietary system, and Deakin leadership and IT personnel were not provided with details on how it works, indicating low transparency. Opacity and explainability are not possible to assess. The output (responses to user questions) appears interpretable. "*Deakin did not learn how the technology classifies natural language"* (Scheepers et al., 2018, p. 102)	High: training Watson for Deakin required the development of a list of paired questions and answers based on the Deakin context. The quality of this data needed to be maintained at the source during operation. *"The university had to assign a single content owner responsible for each subject area and have them provide the correct answers. For Watson's first public release, 100 content owners from across all Deakin's campuses composed all of the answers to ensure accuracy and appropriateness"* (Scheepers et al., p. 93).	Low: Watson is a rule-based system, and thus, responses are based on the training dataset and the source data.	High: Watson was designed to operate autonomously, answering student questions in the place of staff. *"'Watson is always up and running, making services available to students at any time'"* (Scheepers et al., 2018, p. 98).	No link or connection was explicitly evident based on evidence from the case.
4. NeuroYou	Medium: the system was legally required to be explainable, but it was still opaque. The developer shared system details with the users	High: the system needed to be trained on local data to be calibrated to the MultiCo context, and additional data regarding hiring decisions needed	High: the system output often did not reflect the hiring managers' expectations; the system recommended	Medium: the system autonomously creates a shortlist, excluding many candidates, but the shortlist is reviewed	Limited explainability was overcome by transparency and interpretability. This was possible because of developer openness,

	(transparency), and the PA team was able to interpret the output. *"[The ML developers] eventually decided on linear techniques* *because of the importance that the algorithm be explainable and legally accountable in the HR domain."* (van den Broek et al., 2021, p. 1569).	to be incorporated for training. The system was operated using data generated from candidates playing online games. *"The developers constructed the training dataset by including HR's professional standards on useful attributes and performance indicators"* (van den Broek et al., 2021, p. 1569).	candidates the hiring managers would have rejected. *"When the developers presented the model to the HR team, the experts were surprised that the algorithm had discovered several relationships that were at odds with their usual views"* (van den Broek et al., 2021, p. 1570).	by humans to inform hiring decisions. *"Senior managers had the algorithmic predictions on candidates during the interviews and made the final hiring decisions"* (van den Broek et al., 2021, p. 1571).	shown during meetings with the client. "*The developers began to consider HR's insights as valuable additions to the model, so they made several changes to the variables in the model"* van den Broek et al., 2021, p. 1571).
5. ShipCo	Low: system details were shared with the user, the data scientist and analyst audited the algorithm regularly, and the system output could be interpreted. *"During this phase, the CDO called for meetings with the data scientist and the researcher to evaluate output from the algorithm"* (Gronsund and Aanestad, 2020, p. 8).	High: the system required granular AIS data and clean data, both for training and operation. *"As the team started to look into the AIS data, they realized that the quality of data was insufficient to fully automate the data processing directly"* Gronsund and Aanestad, 2020, p. 8).	Low: during development, the system would return unexpected results, but these were resolved before deployment. *"When an issue with the data was detected, such as the port names, the* *data scientist would set out to collect all known portmanteaus, abbreviations and acronyms related to the port in question. He would then instruct the algorithm to manipulate these various strings of port spellings and geographical data, so that it could automatically*	Medium: the system was designed to ultimately replace the researcher, autonomously developing trade tables. However, analysts/brokers would still interpret the results and act on them. *"'Today we are using data-supported human analysis. I want the opposite. I was human-supported data analysis'"* (Gronsund	The autonomy of the system meant that the researcher's role would likely change in the near future. This role change was not documented in the case, however.

			normalize cases of data anomalies" (Gronsund and Aanestad, 2020, p. 8).	and Aanestad, 2020, p. 10).	
6. Readmission Risk Tool	Medium: the developer transparently shared details of the system, but users had difficulty interpreting the output. Explainability and opacity were not discussed in the case. *"Care managers did not fully grasp what kind of data was being collected and how it was being used to generate recommendations. Population Health care managers were also having trouble making sense of the risk scores … Developers addressed this by explaining the risk score: 'We did a crosswalk for care managers where we showed them what is one possible equivalent of red, yellow, green with our model'"* (Singer et al., 2022, p. E29).	High: for the system to accurately predict readmission risk, both numeric and free-text data needed to be included in the model both for training and operation. The system required local patient data for operation. *"The Readmission Risk Tool was developed using a random forest algorithm on inpatient data from 54,000 inpatient discharges"* (Singer et al., 2022, p. E23).	Low: during development, the system would return unexpected results, but these were resolved before widespread use. *"'[Developer from WMC Health] asked to talk to me because are managers using the too that [the developers] were building were challenging [the developers]…Behavioral health patients were onsistently clustered and showing up at the top of the care managers' lists, which presented a dilemma to [the developers], so they called for my thoughts on how to handle it'"* (Singer et al., 2022, p. E25).	Low: the system generated predictions of readmission risk, but the care managers acted on the predictions. "The predictive model creates a patient work list, stratified by risk and paired with additional information from the electronic health record" (Singer et al., 2022, p. E23).	No link or connection was explicitly evident based on evidence from the case.

7. Low Bed Tool	Low: the developer shared system details, and the user could interpret the output. Explainability and opacity were not discussed in the case. *"The Low Bed Tool was developed using an exponential smoothing algorithm on years of historical hospital census data to learn trends and patterns"* (Singer et al., 2022, p. E23)	High: the system required local data for training and operation. The data needed to be collected in a uniform format to be usable. *"The Low Bed Tool was developed using an exponential smoothing algorithm on years of <u>historical hospital census data</u> to learn trends and patterns"* (Singer et al., 2022, p. E23)	Low: during development, the system produced unexpected results, but these were resolved prior to deployment. *"'The first time that [developers] came to me … I just didn't understand what I was seeing because it didn't match up with my intuition, but I knew the model wasn't quite right'"* (Singer et al., 2022, p. E28).	Low: the system produced a prediction, but the human manager acted on the prediction. *"The Vice President of Clinical Care Management and Utilization Management, who is the main user of the tool, reported that it has allowed her to make better decisions to increase bed availability during high patient flow times"* (Singer et al., 2022, p. E23).	No link or connection was explicitly evident based on evidence from the case.
8. Sepsis Watch	Medium: the system was opaque and unexplainable, but details of the system were shared with clinicians and made publicly available through registration as a clinical trial, and the output could be interpreted by users. *"Although there are emerging methods to improve explainability of RNNs, end users cannot*	High: the system required high-quality local data for training and needed to be connected to patient EHRs for operation. *"The first challenge was to curate local EHR data to better understand the problem and to build out the relevant data elements to train the machine learning model"* (Sendak et al, 2020b, p. 103)	Medium: sometimes, the system would make predictions that contrasted with physician expectations, and physicians did not always trust the system outputs. *"However, ED physicians described relatively less trust in the model. They thought certain components of the Sepsis Watch algorithm were too heavily weighted (e.g.* blood cultures*). Physicians also noted that Sepsis Watch both missed some important sepsis cases and had*	Low: the system autonomously produced predictions of sepsis risk, but clinicians decided whether to act on the predictions. "*No patient was put on the* Treatment *page without independent review and confirmation by the attending physician"* (Sendak et al., 2020a, p. 7).	The opacity of the system and the unpredictability of the output impacted physician trust in the early stages of implementation. *"However, ED physicians described relatively less trust in the model. They thought certain components of the Sepsis Watch algorithm were too heavily*

	contemplate the entire model and cannot reliably understand the relationships between model inputs and outputs. As such, there was not a deliberate effort to explain the MGP-RNN model output" (Sendak et al., 2020b, p. 103).		*false positives"* (Sandhu et al., 2020, p. 5).		*weighted (e.g.* blood cultures*). Physicians also noted that Sepsis Watch both missed some important sepsis cases and had false positives"* (Sandhu et al., 2020, p. 5).
9. Anamnesis	Medium: the system was opaque and not explainable, but system details were shared with users. "*The agent's functionality was based on structured questions and anamnesis questionnaires that already existed in the hospital"* (Reis et al., 2020, p. 287).	High: the system needed to be trained on EHR data and on patient-physician interactions. *"As more and more labeled data is stored, the dataset for the algorithms would grow and the process would improve"* (Reis et al., 2020, p. 284).	Not mentioned, as the system was not in operation.	High: the system was designed to autonomously create documentation that physicians would be liable for, but the physician could decide whether to accept the agent's recommendation. *"The use case was very clear. The cognitive agent would automate the documentation of anamnesis and treatment in a three-step process…The physician could accept or modify the cognitive agent's proposal"* (Reis et al., 2020, p. 284).	System autonomy limited physician willingness to use it, and the inability to fulfill the requirement for detailed data prevented implementation. Fear of loss of expertise and critical thinking due to overreliance. *"Because they were not able to interact with the cognitive agent during anamnesis and documentation, they felt like they could not confirm or change the results of the anamnesis generated by the agent. As a consequence, they perceived the cognitive agent as invasive rather*

					than as a support tool, which was a major reason for them resisting its implementation" (Reis et al., 2020, p. 287). *"If a cognitive agent could fully automate anamnesis and documentation, physicians worried tht future generations of physicians would become dependent on AI"* (Reis et al., 2020, p. 291).
10. Robodebt	Medium: the system was explainable and not opaque, and the outputs were interpretable, but system details were not shared with relevant stakeholders (lack of transparency). *"Due to inaccurate and spurious debt-identification methods, even government employees have not always been able to explain how a given debt has been calculated and whether it reflects*	High: the system required accurate data to calculate welfare overpayment. *"The OCI system drew data from two different government systems, one belonging to Centrelink and another one to ATO"* (Rinta-Kahila et al., 2022, p. 318).	Low: unexpected errors in the output were a result of data quality, not driven by learning, and this appeared quickly understood. *"These inconsistencies [in the data] critically limited the extent to which the raw data could serve as a basis for conclusions about a given customer's welfare debt as 'the information to enable an accurate debt assessment to be made' was insufficient"* (Rinta-Kahila et al., 2022, p. 323).	High: the system was designed to autonomously calculate welfare overpayments and inform citizens. Human oversight was removed. *"As part of the government's 2016 campaign promise, they pledged to crack down on 'welfare fraud' by ramping up the use of ADM to fully automate the detection and collection of welfare overpayments"* (Rinta-	System autonomy and lack of oversight resulted in erroneous predictions that were damaging for citizens and government reputation. *"Algorithmic bias embedded in the debt letters triggered widespread citizen distress"* (Rinta-Kahila et al., 2022, p. 324). *"Sustaining the programme under such criticism damaged the*

	reality" (Rinta-Kahila et al., 2022, p. 318).			Kahila et al., 2022, p. 320). *"Minimising human oversight entailed full automation of debt-collection processes and put the machine at the centre of the previously human-centred and largely manual process"* (Rinta-Kahila et al., 2022, p. 322).	*reputation of Centrelink, DHS, and the government"* (Rinta-Kahila et al., 2022, p. 326).
11. CleverLoan	Medium: the system was opaque, and developers were not willing to share details. The output was explainable and could be easily interpreted by users. *"If the decision is to reject a loan application, the system automatically generates a guideline explaining the rejection … AI Provider keeps the building blocks of its AI system strictly confidential and does not share them with any Main Finance managers or employees"* (Mayer et al., 2020, p. 243).	High: the system required high-quality detailed data for training and operation. *"It combines dynamic and static customer characteristics…the system connects with external databases such as those containing customers' account balances or the SCHUFA to gather data on customers' income, assets or debts"* Mayer et al., 2020, p. 243).	Medium: experienced consultants noted that some system outputs were different from their own assessments. "This perception arises from the AI system's ability to learn, which means the decision-making factors are continuously changing. … The unpredictability further increases loan consultants' perceived differences between their own assessments and the AI system decisions" (Mayer et al., 2020).	High: the system was designed to automatically approve or refuse a loan application with no override capability by the consultants. *"Now, with the CleverLoan system, Max makes an appointment to meet with Tom and explains his request. Tom types the data from Max's identity card into the CleverLoan system and fills in the required fields. He clicks on 'Make Request' and, within a few minutes, Tom has the final*	Opacity and autonomy were mentioned as risks of loss of critical thinking and organizational knowledge. *"The transfer of decision-making responsibility to the CleverLoan system has resulted in an increasing number of employees who have lost the ability to reflect critically on their work"* (Mayer et al., 2020).

				decision" (Mayer et al., 2020, p. 244).	
12. Rayfood	No information was provided in the case.	High: the system required high-quality consistent data to operate. *"During the interviews, it appeared that the biggest challenge in the implementation of the AI program was the lack of standardized format in the data"* (Camaréna, 2022, p. 8).	No information provided in the case.	Low: the system processes data sheets to provide information to school districts, but humans make decisions. *"The data and the menu planning tool it supports have since been rolled out to schools as a pilot project. Schools can access a vendor portal, which allows menu planners to (1) pick food items and create recipes, (2) plan meals … (3) set meals to a schedule … (4) connect menus to local sites … (5) track menus to sites …and (5) automatically generate meal … reports" (Camaréna, 2022, p. 10).*	No link or connection was explicitly evident based on evidence from the case.

Appendix I: Evidence and Outcomes of Dataset Curation

Table I-1 Evidence and outcomes of Dataset Curation

Case	Dataset Curation	Evidence	Outcome
1. CAS	A dataset was constructed at the outset of the project using extensive local data.	"For the CAS algorithm to learn, the data scientists constructed a dataset with historic high-impact crime data. [Using three years of historic data], they used bi-weekly reference moments…Each line of data consisted of eight technical variables and 47 predictive variables (limited by strict data regulations)." (Waardenburg et al., 2022, p. 63)	A local dataset was constructed that could predict crimes based on locally relevant data. "The model was thus able to autonomously learn and generate predictions" (Waardenburg et al., 2022, p. 64). Addressed **learning-driven data dependency.**
2. COMPAS	To ensure COMPAS represented the local population, the original model needed to be fine-tuned. The system was initially tested on the local prison population to determine their needs.	"As we have learned researching the implementation in a rural county in Wisconsin, they initially used the ADM trained with data from a densely populated area in California, before the algorithm was adjusted several months later" (Haeri et al., 2022, p. 33) "Initially testing the functions of COMPAS, it was first applied to the Eau Claire jail population: *'I needed to get this process moving…said Let's try it out on our jail population. So my program director at the time […], she interviewed everyone, she did a, she went to all the trainings and did an interview on every person that was in jail, so we could get a baseline as to what the top criminogenic needs were*'" (Hartmann and Wenzelburger, 2021 p. 277).	Training the model on relevant data helps ensure its appropriateness in a given context. The test with the local prison population determined the feasibility and applicability of using the COMPAS tool in Eau Claire. Addressed **learning-driven data dependency.**
3. Watson	A dataset was developed to train Watson that included common student questions and the	"Stage 1 involved collecting students' questions. The Deakin project team gathered nearly 20,000 questions from staff and	The dataset ensured that the answers Watson would provide to

	answers to the questions. The source data for the answers was also improved during this process.	administrators…From the initial collection of questions, 2,000 were selected for the first release of Watson. "In Stage 2, the correct answers to each of the 2,000 questions were formulated. This content could come from many sources: verbal answers from experts, written responses in emails and documents, or multimedia content posted on webpages (Lacity et al., 2018, p. 93)	students would be accurate and reflect Deakin information. Addressed **learning-driven data dependency.**
4. NeuroYou	Data on desirable qualities was collected from HR professionals and integrated into the system. The developers also asked MultiCo to provide performance reviews as a measure of successful candidates. Additional data on hiring decisions was required to develop the system. This data was collected by codifying the hiring decision process.	"For example, to decide which personality traits and skills were important to assess, the developers asked the experts to provide them with job descriptions that included trainees' desirable qualities and statements about MultiCo's company culture… These descriptions helped developers to infer which attributes were relevant to training the algorithm. For instance, the trait 'leadership' was frequently emphasized, so the developers incorporated this trait into the dataset" (van den Broek et al., 2021, p. 1568-1569). "The HR team decided to give the developers the annual performance reviews, which they thought represented the most holistic assessment of employees' performance" (van den Broek et al., 2021, p. 1569). "*'There's a big change I have introduced here, which is to write comments in the [NeuroYou] tool. Previously, we only voted yes or no. This time I also ask you to put comments in the tool for two reasons. First, those comments are the most valuable feedback to candidates. Thinking about the candidates' experience, this is the best they can take out of the experience, that our highest leadership has taken the time to give them comments. Another thing that's important is to challenge ourselves about what we need and want from the candidates. The more you put in the comments, the more help you provide me in knowing what you*	The training dataset for the NeuroYou system was enriched and allowed the system to make predictions that were more relevant to MultiCo. Through the introduction of collecting comments on hiring decisions, the system was able to reveal unexpected patterns in decision-making, such as an anchoring bias. Addressed **learning-driven data dependency.**

		expect from the candidates'" (van den Broek et al., 2021, p. 1572). "MultiCo's managers agree to provide internal data and in order to generate this the human resources (HR) professionals approach 300 employees, asking them to play online games based on neuroscientific insights. The games are used to measure character traits such as their ability to concentrate, emotional intelligence and leadership qualities…. By letting the employees play these online games, the external developers thus gain access to data of 300 internal employees which can be used to specifically train its algorithms. "Along with the efforts of the employees, the HR professionals also provide performance data (that is, data on how well each employee performs) on the 300 employees to NeuroYou. In this way, scores for the online games … can be linked to the performance of the employees, which makes it possible to measure which scores are achieved by successful employees. The profile of the successful employees is then used to calculate to what extent the scores of an applicant correspond to this. Accordingly, based on supervised learning and data on MultiCo's own employees, NeuroYou develops a predictive model about which applicants should and should not be hired" (Waardenburg et al., 2021, pp. 53-54).	
5. ShipCo	Cleaning the data was important in this case. For example, many instances of the same port were spelled in different ways in the dataset. The system also required more granular input data, which prompted subscription to a more frequent AIS feed.	"Realizing that they needed to obtain control over data quality, rather than rely solely on intermediary providers' representation of the data, ShipCo approached a satellite operator and data supplier that collected and offered a stream of AIS data as a service. To achieve a more fine-grained and accurate picture of activity in the oil freight segment the company subscribed to a higher frequency AIS data stream, going from daily to hourly updates" (Gronsund & Aanestad, 2020, p. 7)	Subscribing directly to the data stream allowed ShipCo to bypass third-party providers and have access to a near-real-time stream. This higher-quality input data allowed them to improve the quality of their analysis.

		"When an issue with the data was detected, such as the port names, the data scientist would set out to collect all known portmanteaus, abbreviations and acronyms related to the port in question. He would then instruct the algorithm to manipulate these various strings of port spellings and geographical data, so that it could automatically normalize cases of data anomalies" (Gronsund & Aanestad, 2020, p. 8)	Addressed **learning-driven data dependency.**
6. Readmission Risk Tool	During development, the need to include certain elements that were captured in free text (e.g., social determinants of health) became apparent. The dataset also included overinflated readmission rates that needed to be adjusted.	"'*Not all (of the key data) is encapsulated in the risk score. There are many different issues that the care managers have to assess that might not be reflected in the score, e.g., what's the patient's knowledge, can they verbalize discharge instructions, can they get to their appointments, are they connected to a PCP (primary care physician)*' (Readmission Risk Tool User)" (Singer et al., 2022, p. E26). "'*The tool was not capturing those [social determinants of health], so we asked how do you bring that data in …. We learned that the tool cannot capture that, because it's in the care manager notes, these aren't discrete fields*.' (Readmission Risk Tool Developer)" (Singer et al., 2022, p. E26). "The initial risk tool, however, did not enable them to predict as well as they would have liked, because crucial information, such as availability of family caregivers, was in text rather than numeric form and could not be captured in the ML-based model" (Singer et al., 2022, p. E27). "One problem that arose was that there were many different issues that the Population Health care managers wanted to assess that were not reflected in the risk score because they were captured in free text form rather than numerical form. Another problem was that the developers realized some of the data they had been including in the model should not have been included. The model had inflated readmission rates because the developers had unintentionally counted internal transfers as readmissions. Thus,	Including the elements in free text enabled the tool to be more accurate, relevant, and useful. Addressed **learning-driven data dependency.**

		the Readmission Risk Tool involved a significant amount of back and forth between the ML technology, the developers, and the users, as the different groups worked together to identify and address discrepancies in the data" (Singer et al., 2022, p. E28). "'*So, (in addition to developing the model), we developed a tableau dashboard so that the care managers could see not only the readmission risk score, but also other key data about patients that informed care manager decisions regarding which patients to call'* (Readmission Risk Tool Developer)" (Singer et al., 2022, p. E26).	
7. Low Bed Tool	The data required for the system was collected in different ways by different people and needed to be harmonized.	" *It turned out that different groups collected data on beds to answer different questions, like what is the length of stay, how do we track transfers…so everyone (collects) data in different ways'* (Low Bed Tool user)" (Singer et al., 2022, p. E26). "*'We had to come to an agreement with (end user) about what we were going to collect before we could move forward. This took a long time to reconcile, but it ended up being a great way to get everyone on the same page'* (Low Bed Tool developer)" (Singer et al., 2022, p. E26). "As a result of this data reconciliation process, certain groups subsequently altered how they were measuring bed availability in order to be better aligned with one another" (Singer et al., 2022, p. E28).	Ensuring data was collected in the same way by all parties improved the accuracy of the system output. Addressed **learning-driven data dependency.**
8. Sepsis Watch	Local data was used to train the system rather than data from other locations, to ensure the specificity of the hospital population. The system needed real-time data to ensure that	"Local data was carefully curated and the solution needed to work effectively in the local context" (Sendak et al., 2020b, p. 104). "Data were curated from the local quarternary academic hospital with over 1,000 beds and over 40,000 inpatient admissions per year. In total, the model development and evaluation dataset	Using real-time patient data ensured the system could predict sepsis in a relevant time frame. Connecting the patients' EHR ensured that their personal health information could be included in predictions of sepsis.

	sepsis detection could occur in real time.	contained over 32 million data points" (Sendak et al., 2020b, p. 103). "The model pulls data from the electronic health record (EHR) and is updated every hour to ensure real-time analysis of sepsis risk" (Sandhu et al., 2020, p. 2).	Addressed **learning-driven data dependency.**
9. Anamnesis	The system required detailed historical records of patient-physician interactions to be properly trained, but physicians were unwilling or unable to provide this data.	"The test version used patient data stored in the hospital's EHR system" (Reis et al., 2020, p. 286). "This is a chicken-and-egg problem: without extensive, broad and longitudinal data collected from experienced physicians using a cognitive agent, the agent will not be able to perform well enough to convince physicians of its value. Bu tits low performance makes physicians unwilling to train and use the cognitive agent. The highly complex process of establishing a database of reliable standardized data would take years and would likely require significant governmental support, cooperation across multiple and diverse hospital groups, and very large volumes of patient data" (Reis et al., 2020, p. 289).	The inability to curate the data required for the system was one reason why the system implementation did not proceed. By not including all important data, **learning-driven data dependency** was not addressed.
10. Robodebt	The system's data was faulty, and discrepancies were not addressed.	"The OCI system drew data from two different government systems, one belonging to Centrelink and another one to ATO. These two systems recorded citizens' income data in different formats – while Centrelink's system applied fortnightly figures, ATO's stored annual income data. OCI averaged a citizen's earnings reported to ATO over a series of fortnights, matched them with received welfare benefits, and based on the matching, calculated potential overpayments" (Rinta-Kahila et al., 2022, p. 318). The data that was provided to OCI's algorithm as a basis for its decision-making was inconsistent mainly for two reasons. First, the two data sources, Centrelink and ATO, recorded data in different and incompatible formats (fortnightly vs. yearly). Moreover, the name of the same employer was sometimes	Not addressing discrepancies meant that the system made inaccurate predictions of debt. By not properly curating and combining data sources, **learning-driven data dependency** was not addressed.

		recorded in a different way between the two databases, e.g., if a customer had made a spelling mistake when declaring their income to either party. These inconsistencies critically limited the extent to which raw data could serve as a basis for conclusions about a given customer's welfare debt as '*the information to enable an accurate debt assessment to be made*' was insufficient (Rinta-Kahila et al., p. 323).	
11. CleverLoan	The Provider required increasingly more data from the Bank to develop the CleverLoan system. One additional datapoint was hiring decision information. This data needed to be codified so it could be input into the AI system.	"As a result, the ML Provider introduced a new loan application form in which only data fields required by the bank were included. The intention was to use data entered via this form to train the model: '*The problem was that [Bank] had never really kept track of how they made the decision. It was super individual, depending on the consultant. And then, you could see which customer paid back the loan and who didn't. But there was no consistent documentation and thus, it was difficult to track back the exact reason for the default rates' (Sales manager, Provider)*" (Mayer et al., 2024, p. 6710). "Regardless of whether Bank consultants followed the ML model recommendation, the Bank required them to record their decision (whether or not they followed the ML recommendation) and the T&Cs of any loan. … Over time, the ML Provider extended the range of data fields the Bank consultants needed to populate in the system. … This information … combined with the consultant's actual decision regarding the T&Cs of the loan, provided the data needed by the ML Provider to further improve the ML model so that it would provide more accurate recommendations in the future" (Mayer et al., 2024, p. 6710-6711). "The Provider learned that the residential address of a customer or their nationality can also influence repayment behavior. Thus, the Provider added new data entry fields into the loan application form to gain more information about customers" (Mayer et al., 2024, p. 6711).	The increased data points improved the accuracy of the ML system: "As a result, the ML model became increasingly accurate. This was evident in the decreasing loan default rates" (Mayer et al., 2024, p. 6711). Addressed **learning-driven data dependency.**

		"Another important development was the Provider's cooperation with external providers such as SCHUFA, which provides information on customers' credit histories" (Mayer et al., 2024, p. 6711). "'*There's a big change I have introduced here, which is to write comments in the [NeuroYou] tool. Previously, we only voted yes or no. This time I also ask you to put comments in the tool for two reasons. First, those comments are the most valuable feedback to candidates. Thinking about the candidates' experience, this is the best they can take out of the experience, that our highest leadership has taken the time to give them comments. Another thing that's important is to challenge ourselves about what we need and want from the candidates. The more you put in the comments, the more help you provide me in knowing what you expect from the candidates'*… "Consequently, a key expert hiring practice that involved a lot of social interaction was transformed so the developers could find the categories that played important roles in managers' judgement of candidates" (van den Broek et al., 2021, p. 1572).	
12. Rayfood	To improve the system, food suppliers were advised to standardize their documentation.	The lack of a standardized format in the input data "resulted in a large amount of time spent between the digitization team and LPB and Rayfood Solutions clarifying which keywords to look for and to ensure the extracted data was accurately matched to the data fields requirements. This, in turn, created challenges for the Rayfood team, who had to contact the suppliers and request clarifications on how the fields in their product specifications sheets matched (or did not match) the compliance reporting in the USDA standards" (Camaréna, 2022, p. 8). "However, interviews with representatives from LPB indicated that once Rayfood were faced with questions of data validation, data standardization, and consistency of language, the project	The system had an accuracy rate of 95-98%. At the same time, the study also notes that "additional information about how the relationships were influenced by the project and what benefits this could lead to was not available in the material" (Camaréna, 2022, p. 10). Addressed **learning-driven data dependency.**

		coordinators realized that they had a new role to play in the supply chain" (Camaréna, 2022, p. 10).	

Appendix J: Evidence and Outcomes of User Demos

Table J-1 Evidence and Outcomes of User Demos

Case	User demonstrations	Evidence	Outcome
1. CAS	None mentioned		
2. COMPAS	None mentioned		
3. Watson	Preliminary demonstrations of how the system would work; demonstrations of performance on local data	"In mid-2014, IBM personnel visited Deakin's Vice-Chancellor and Deputy Vice-Chancellor to demonstrate Watson. They could immediately see the potential value, but they needed to learn more so engaged IBM to do a cognitive value assessment. After that exercise, the Deakin administrators concluded there was enough potential value to pilot the new technology within a limited domain" (Lacity et al., 2018, p. 92).	Better understanding of how the system worked and what it could do. Understanding of how and why to customize the system for Deakin. Addressed **autonomy.**
4. NeuroYou	Meetings with users during ideation regarding data curation, to provide demonstrations of performance and to collect input for future iterations.	"In the fall of 2017, Marvin ran several product demonstrations for MultiCo's HR team to show how NeuroYou's tool offered a superior way of judging job candidates. To provide evidence of this claim, NeuroYou ran a small-scale pilot on two groups, comparing 250 candidates for the trainee programs with 40 successful trainees in the organization" (van den Broek et al., 2021, p. 1567). "When the developers presented the model [a later version] to the HR team, the experts were surprised that the algorithm had discovered several relationships that were at odds with their usual views. … In several cases, the patterns the algorithm discovered triggered the experts to reflect on the limitations of insights that were based on historical data if they wanted to develop hiring strategies for the future" (van den Broek et al., 2021, p. 1570).	Better understanding of how the system worked and what it could do, better understanding of how and why the inclusion of additional data would improve the system. Addressed **learning-driven unpredictability.**

5. ShipCo	Regular meetings between technical developers and users to demonstrate progress and resolve data quality issues.	"As the team started to look into the AIS data, they realized that the quality of data was insufficient to fully automate the data processing directly" (Gronsund & Aanestad, 2020, p. 7). "During this phase [enrolling domain expertise to audit algorithmic output], the CDO called for meetings with the data scientist and the researcher to evaluate output from the algorithm. The data scientist would present algorithmic results in the form of complete tradetables and map plots of ship voyages. During the discussion the team would zoom into specific voyages to resolve data disparities. The data scientist would examine the underlying code, switching between an Emacs and a SQL editor as well as an interactive maritime map" (Gronsund & Aanestad, 2020, p. 8).	Demonstration of system limitations in early stages, improving understanding of how the system worked. Addressed **inscrutability.**
6. Readmission Risk Tool	Meetings with users to demonstrate progress, incorporate feedback, and address data quality issues.	"Developers engaged in further discussion with care managers to understand how they might be able to provide not only the readmission risk score but also other key data about patients that could inform care manager decisions regarding which patients to call" (Singer et al., 2022, p. E27). "Iteratively coengaging individuals around the Readmission Risk Tool also required back-and-forth discussion between developers, users, and outside experts" (Singer et al., 2022, p. E28).	Improvement in understanding of system capabilities and limitations, incorporation of additional data. Addressed **inscrutability.**
7. Low Bed Tool	Several meetings with the end user to identify and confirm use case, to demonstrate progress, and to incorporate feedback.	"*'The first time that (developers) came to me, I couldn't tell them what I wanted. I just didn't understand what I was seeing because it didn't match up with my intuition, but I knew that the model wasn't quite right. They went back—the (developers) and my team—went side by side to try to find out why the disparity (between my existing census report and the Low Bed Tool) was happening'*" (Singer et al., 2022, p. E28).	Understanding of appropriate use case for the system, fine-tuning of the system. Addressed **learning-driven unpredictability.**
8. Sepsis Watch	Meetings with users to demonstrate progress and incorporate feedback.	"Clinical experts specified and reviewed representations of all data elements used by the model. Once the final model was developed, multiple iterations of chart reviews were completed to finalize the threshold used to classify high risk patients. Two RRT	Ensuring system meets the needs of users and respects clinical requirements.

		nurses reviewed multiple versions of the user interface and clinical experts reviewed and confirmed patient records retrospectively identified as high risk of sepsis and meeting sepsis criteria" (Sendak et al., 2020b, p. 105). "Monthly meetings were held throughout the pilot to review progress, address concerns surfaced by front-line staff, and make decisions about changes to workflow" (Sendak et al., 2020b, p. 105). "User interface designers repeatedly met with RRT nurses to iterate on functions, information, control, and visual components of the design. …. Sepsis Watch was originally conceptualized as a dashboard to display model output; however, feedback and iterations led to the development of a highly interactive workflow management solution" (Sendak et al., 2020a, p. 7).	Did not explicitly address the characteristics of AI.
9. Anamnesis	Demonstration of proof of concept to physicians to show system capability and current limitations. The system was demonstrated after an end-to-end version had been developed, not during intermediate stages.	"The project team tested the cognitive agent intensively to guarantee its technical abilities. They then presented the test version to physicians in a series of workshops where they simulated the use cases interactively. After the workshops, physicians provided feedback about application scenarios perceived as relevant." (Reis et al., 2020, p. 286). "The anthropomorphic design of the cognitive agent created the illusion that the patient was interacting directly with a virtual entity, which, in turn, created the impression that the virtual entity had medical expertise. Physicians were concerned that providing this type of patient care could oversimplify the medical profession, turning an individual examination of a patient into a standardized procedure." (Reis et al., p. 290)	The users were able to see a pilot version of the system to assess its usefulness, relevance, and acceptability in their context. By demonstrating a complete version, physicians were unable to voice concerns about inscrutability and autonomy early in development. Absence of early demos limited ability to address **inscrutability** and **autonomy.**
10. Robodebt	No user demonstrations mentioned. Lack of user input cited as a reason for failure.	"As such, little testing or piloting was conducted when implementing the system: '*We asked DHS whether it had done modelling on how many debts were likely to be over-calculated as*	No demo.

		opposed to under-calculated. DHS advised no such modelling was done"" (Rinta-Kahila et al., 2022, p. 323).	Absence of demo limited ability to address **autonomy.**
11. CleverLoan	It appears as though meetings occurred, but there is no mention in the case studies about the content or function of the meetings.		NA
12. Rayfood	Frequent interactions (not demos) between developers and users to resolve data quality issues.	"On many occasions during our observation of the digitisation operators, the operators engaged in conversations to share knowledge about food and try to make sense of the definitions for the data fields. For example, one of the data was called "dark green vegetables". In a multicultural environment, the team was often unsure of which vegetable should be considered "dark green" and which to consider "green". The name of vegetables themselves were unknown to some of the team members; once one person researched it and found photos, they would share the knowledge with others." (Camarena 2022., p. 10).	Improved developer understanding of the context of the system. Did not explicitly address the characteristics of AI

Appendix K: Evidence and Outcomes of Developer Openness to Integrating User- or Domain-Driven Change

Table K-1 Evidence and Outcomes of Developer openness to integrating user- or domain-driven change

Case	Developer openness	Evidence	Outcome
1. CAS	NO: The developers were <u>resistant</u> to integrating user-driven changes.	"Taking their assignment to create connections between the machine learning community and the police community seriously, the intelligence officers unsuccessfully tried to share their findings from the police data with the data scientists. For example, when they [the intelligence officers] suggested a different method for calculating time frames, the data scientists maintained their belief in the machine learning techniques they had applied and said that this was the 'only scientifically proven method' for calculating time predictions (data scientists Dennis and Mary). In another instance, when one of the intelligence officers emailed the data scientists to share that CAS generated predictions for car burglaries in areas where cars were not permitted, data scientist Dennis continued to believe in the CAS predictions and answered that 'it really was a parking area' (Waardenburg et al., 2022, p. 72)	The intelligence officers were frustrated with their inability to interpret the CAS output and provide relevant recommendations to the police managers. Lack of developer openness to integrating user- or domain-driven change meant **inscrutability** was not addressed.
2. COMPAS	Not mentioned		
3. Watson	LIMITED: The IBM team shared limited information about how the system worked	"Deakin learned enough about Watson's functional components and architecture to optimize its performance and to provide ongoing support" (Lacity et al., 2018, pp 101-102.	Deakin acquired sufficient knowledge to operate the system autonomously. Did not explicitly address a characteristic of AI.

4. NeuroYou	The developer actively engaged with the client on multiple occasions to integrate their insights and needs, even though the resulting model was less accurate as a result, according to the developer.	"This deviation from their initial pursuit of independence was triggered by their confrontation with a data-selection problem, when the developers needed the experts to help them decide what employee data was useful to select for the algorithm" (van den Broek et al., 2021, p. 1569). "The developers realized that, if they wanted to come to a model that could be meaningfully applied, they would have to overcome the algorithm's nearsightedness" (van den Broek et al., 2021, p. 1570). "The developers coped with the frame problem by engaging with experts to understand their broader vision of how the workforce should evolve over time. Developers held several three-hour meetings with the HR team to evaluate the variables of the predictive model systematically, leaving room for the HR professionals to reflect on the insights that the algorithm had produced" (van den Broek et al., 2021, p. 1570). "The developers began to consider HR's insights as valuable additions to the model, so they made several changes to the variables in the model" (van den Broek et al., 2021, p. 1571). "When the algorithm was up and running, the developers were eager to see how the organization at large took up its insights so the algorithm could be fed with new data and revise its learned patterns over time" (van den Broek et al., 2021, p. 1571) "The developers realized that, if they wanted the managers to take up the algorithmic predictions, they would have to dig deeper into managers' reasoning for selecting candidates during the group interview" (van den Broek et al., 2021, p. 1572). "Finally, the work of the PA team and HR professionals does not stop with translating the AI results for hiring managers. In their role as algorithmic broker, they communicate the adjustments	The resulting model was adapted to the needs and wants of the client. "As a result of the developers' augmenting the predictive model with the experts' vision about the future workforce, the model increasingly converged with how experts judged candidates, leading to a newly shaped model that combined the algorithm's insights with those of the experts" (van den Broek et al., 2021, p. 1571). Addressed **inscrutability and learning-driven unpredictability**.

		they apply to the visualizations to the developers. As a result, the developers make modifications to the AI system, for example, to automatically generate a spider chart. By deploying the HR professionals and the PA team together as an algorithmic broker, MultiCo thus makes adaptive algorithmic brokering possible. The HR professionals are in direct contact with hiring managers, who use the AI system in practice. At the same time, the HR professionals (also after the development phase), through their connection with the PA team, can influence the further development of AI system." (Waardenburg et al., 2021, pp.96-97).	
5. ShipCo	Multiple cycles of development during which the developer (internal data scientist) was always present to demonstrate progress and to integrate feedback.	"During the discussion the team would zoom into specific voyages to resolve data disparities. The data scientist would examine the underlying code, switching between an Emacs and a SQL editor as well as an interactive maritime map. The data scientist explained how he targeted abnormal or unconfident output from the algorithm: 'I passed (edge cases) on to the researcher and one broker for assurance and feedback'" (Gronsund & Aanestad, 2020, p. 8). "In this third version of the configuration, tradetables were generated by both the researcher and the algorithm, and then compared by the data analyst. Only on some occasions where the two reference outputs deviated, the researcher, data scientist or other domain experts were called in. The CDO and the data scientist adjusted the algorithm and allowed it to be released to the intended users, the company's analysts" (Gronsund & Aanestad, 2020, p. 9).	The integration of the broker's feedback allowed the system to develop in a way that met the brokers' needs. Did not explicitly address a characteristic of AI.
6. Readmission Risk Tool	The developers were keen to integrate feedback from users to make the tool more useful and suitable for the users.	"The Readmission Risk Tool was initially conceived as a simple model to identify patients with a high risk of readmission but evolved as users defined target interventions and workflows" (Singer et al., 2022, p. E27).	The tool went through multiple iterations, and in the end was developed according to the needs of the users.

		"'*The tool was not capturing those [social determinants of health], so we asked how do you bring that data in …. We learned that the tool cannot capture that, because it's in the care manager notes, these aren't discrete fields.'* (Readmission Risk Tool Developer)" (Singer et al., 2022, p. E26). "Developers engaged in further discussion with care managers to understand how they might be able to provide not only the readmission risk score but also other key data about patients that could inform care manager decisions regarding which patients to call" (Singer et al., 2022, p. E27). "Iteratively coengaging individuals around the Readmission Risk Tool also required back-and-forth discussion between developers, users, and outside experts" (Singer et al., 2022, p. E28). "Similarly, when developing the Readmission Risk Tool, developers depended on the care managers to use their intuition to provide iterative feedback to the developers regarding the tool's accuracy and possible areas for improvement; in turn, the developers adjusted the underlying ML-based model based on their investigation and the care managers' feedback" (Singer et al., 2022, pp. E28-E29).	Did not explicitly address a characteristic of AI.
7. Low Bed Tool	The developers initially planned to develop a surge prediction tool, but this was not feasible. They pivoted to a low bed tool. They spent a lot of time during ideation and development understanding the user's needs to properly integrate them into the tool.	"*'(The developers) came to me when they found out that their initial project around predicting ER surges wasn't going to work….They asked me if I could use a model to help me manage low bed….We spent a lot of time talking about where the current process was, and where I saw room for improvement'* (Low Bed Tool user)" (Singer et al., 2022, p. E25). "*'We initially spent a lot of time talking to the ED and EICU staff about their needs…(With the dramatic change in the ML model from surge to low bed), we have spent a lot of time talking with the people preparing the Low Bed Tool for the new end user*	By "getting out of the chair" the developer was able to make something useful for the end user. Did not explicitly address a characteristic of AI.

		to ask what the current process is and how it's being used' (Low Bed Tool developer)" (Singer et al., 2022, p. E26). "The developers thus had to engage her in a way that took into account her needs and perspectives, as well as the characteristics of her current technology" (Singer et al., 2022, p. E28). "Instead of trying to convince this user of ML tool's merits, the tool developers emphasized that they could adapt the technology to fit her current needs, workflows and expectations" (Singer et al., 2022, p. E28). "*'We're trained to develop models. But, without (end user) who has direct experience, we could not develop the model…As a (developer), I tend to stay in the chair. But, doing this project required that we get out of the chair, and gain familiarity with the subject of analysis'* (Low Bed Tool developer)" (Singer et al., 2022, p. E27)	
8. Sepsis Watch	The development team sought out input from physicians and nurses throughout development, beginning with ideation.	"Two nurses were involved in the design and development of the system and provided feedback on training materials developed for the pilot" (Sendak et al., 2020, p. 105). "Clinician preferences were incorporated to optimize the ease of use and utility for end users" (Sandhu et al., 2020, p. 8).	The constant integration of feedback from the clinical team helped favor the acceptability of the system. Did not explicitly address a characteristic of AI.
9. Anamnesis	Does not appear so. When the physicians pushed back on the project, their feedback was not integrated. Instead, the project was abandoned.	"Despite such positive feedback, there was still a great deal of skepticism. Although the physicians acknowledged that complementary knowledge supporting a diagnosis decision is valuable to themselves and patients, they refused to approve the project. Among other causes of resistance, they were especially worried about the engagement function of the cognitive agent. … After nine months of developing the use case and the test version and six months of technological testing, the project team realized the hospital's physicians did not want to use the	The project was postponed indefinitely, and there was no mention of planned integration of physician feedback and criticism in a future version of the system. Lack of developer openness to integrating user- or domain-driven

		cognitive agent. The team therefore decided to postpone the project indefinitely until it had a better understanding of the reasons for the physicians' rejection and what steps to take to ensure future project success" (Reis et al., 2020, p. 287).	change meant **autonomy** was not addressed.
10. Robodebt	[Not clear if this refers to the developers or the client, but refusal to integrate user feedback is evident.]	"Centrelink employees who raised red flags before OCI was implemented had their warnings dismissed by the department management: '*Many members stated that concerns were raised during the design process but were simply ignored*'" (Rinta-Kahila et al., 2022, p. 323). "As such, little testing or piloting was conducted when implementing the system: '*We asked DHS whether it had done modelling on how many debts were likely to be over-calculated as opposed to undercalculated. DHS advised no such modelling was done*' (Ombudsman)" (Rinta-Kahila et al., 2022, p. 323). "**Managerial myopia** (i.e., decision-makers' shortsightedness or "lack of imagination, foresight, or intellectual insight"), was reflected in top management's shortterm oriented measures when modifying the OCI system in response to the mounting criticism. Although top management was already pressured to implement modifications in the system after the first wave of negative press in early 2017, the Senate's and Ombudsman's investigations found the changes inadequate. The system received a number of helpful modifications between 2017–2019, including more informative debt notices, improved online interface, mechanisms to filter complex cases for manual processing, and employees' expanded role capacity. These changes did little to address the public outcry, because they did not rectify the system's core problems of speculative calculation of debts and reversed onus of proof." (Rinta-Kahila et al., p. 325)	The system backfired. Lack of developer openness to integrating user- or domain-driven change meant **learning-driven data-dependency** was not addressed.
11. CleverLoan	The client had specific requirements regarding	"For instance, it was important to the Bank that the Provider did not discriminate against certain customer groups by asking for	Despite specific criteria on data and model design to limit

	parameters to include or not include, and these appeared respected by the developer.	personal information such as religion, sexual orientation, or political mindset. Thus, the Bank was interested in understanding which data parameters would be applied in the ML model, and for what purpose” (Mayer et al., 2024, p. 6710).	exclusion, some customers were systematically excluded. (evidence below not directly related to the act of developer openness, more a feature of the algorithm). “The CleverLoan AI system also systematically excludes certain groups of people, based on their social status, origin or place of residence. The system stores and analyzes all available data, such as repayment behavior; asset development and current debts. Based on these characteristics, CleverLoan uses heuristics to determine the loan conditions for entire groups of customers rather than for individuals. For instance, the average income in certain residential areas is included in the analysis. Thus, if the only difference between two otherwise equal applicants is their place of residence, they will receive different loan conditions” (Mayer et al., 2020, p. 251). Developer openness to integrating user- or domain-driven change had limited effect on addressing **learning-driven unpredictability**.

12. Rayfood	LBP (provider) wanted to ensure they got the parameters and data labelling correct and so they sought input from Rayfood, the client.	"This resulted in a large amount of time spent between the digitization team at LPB and Rayfood Solutions clarifying which keywords to look for and to ensure the extracted data was accurately matched to the data fields requirements" (Camaréna, 2022, p. 8)	The system was developed with a clearer understanding of the ingredients (input data). Developer openness to integrating user- or domain-driven change addressed **learning-driven data-dependency.**

Appendix L: Evidence and Outcomes of SMEs

Table L-1 Evidence and outcomes of SMEs

Case	SMEs	Evidence	Outcome
1. CAS	Not mentioned		
2. COMPAS	Not mentioned		
3. Watson	Subject matter experts were the content managers responsible for initial dataset curation and dataset maintenance.	"At Deakin, the subject matter experts across the various campuses are responsible for Watson's content. Traditionally, these experts were responsible for managing web-based content, which has its own particular structure and editorial style. For Watson, the experts needed to write content in a form that a CA system could provide, rather than as web pages that students would read" (Lacity et al., 2018, p. 101)	Ensuring that the data was managed by SMEs was one way of ensuring quality. Assigning SMEs to specific content areas within their expertise also helped ensure the quality of the input data. Addressed **learning-driven data dependency.**
4. NeuroYou	Subject matter experts were included at various stages during development, from constructing training data, building the model and using the model in practice	"To decide which personality traits and skills were important to assess, the developers asked the experts to provide them with job descriptions that included trainees' desirable qualities and statements about MultiCo's company culture" (van den Broek et al., 2021, p. 1568). "Developers held several intensive three-hour meetings with the HR team to evaluate the variables of the predictive model systematically, leaving room for the HR professionals to reflect on the insights that the algorithm had produced" (van den Broek et al., 2021, p. 1570). "Consequently, a key expert hiring practice that involved a lot of social interaction was transformed so the developers could find	Involving domain experts ensured that the dataset for the AI system accurately reflected the client company's use case and was able to capture relevant data. Addressed **learning-driven data dependency.** Involving domain experts helped improve the design of the model and align model outputs better with organizational expectations.

		the cat3egories that played important roles in managers' judgement of candidates" (van den Broek et al., 2021, p. 1572).	Addressed **learning-driven unpredictability.**
5. ShipCo	The Researcher and brokers are brought in to help resolve "edge cases."	"*'I passed (edge cases) on to the researcher and one broker for assurance and feedback. For example, in one case, one vessel reported the same port, Sungai Linggi in Malaysia, for both departure and arrival. What we are interested in is understanding what really happened here so that we can have the algorithm to automatically deal with such cases in the future'*" (Gronsund & Aanestad, 2020, p. 8). "In these meetings [to tune on edge cases] the researcher who carried out the manual data processing and preparation, was a crucial participant" (Gronsund & Aanestad, 2020, p. 9).	Bringing in experts meant that edge cases could be resolved more quickly and more appropriately. Addressed **learning-driven data dependency.**
6. Readmission Risk Tool	Not mentioned.		
7. Low Bed Tool	The SME was the end user, and she was very involved during all stages of development and implementation to provide input.	"The tool developers thus had to engage her [the end user] in a way that took into account her needs and perspectives, as well as the characteristics of her current technology" (Singer et al., 2022, p. E28). "*'We have spent a lot of time talking with the people preparing the Low Bed Tool for the new end user to ask what the current process is and how it's being used'* (Low Bed Tool developer)" (Singer et al., 2022, p. E26).	Involving the end user (SME) and her domain-specific insights ensured that the tool corresponded to her needs. Did not explicitly address a characteristic of AI.
8. Sepsis Watch	Front-line clinicians were involved throughout development.	"Finally, the fourth approach was to engage front-line clinicians directly in the design and development of the model and user interface" (Sendak et al., 2020b, p. 105). "Two ED physicians and the ED nursing director joined the Sepsis Watch team and were closely engaged in workflow and	Involving domain experts ensured that the context of sepsis detection and treatment and the context of the hospital environment were considered.

		design decisions leading up to the launch" (Sendak et al., 2020b, p. 105). "Clinicians specified the most relevant information to accompany the risk level displayed on the Sepsis Watch user interface" (Sendak et al., 2020b, p. 105). "The team assembled to design, develop, and integrate Sepsis Watch into routine clinical practice included a full-time innovation team, as well as implementation experts, machine learning experts and clinical experts" (Sendak et al., 2020b, p. 104).	Addressed **learning-driven data dependency.**
9. Anamnesis	The medical director was the domain expert and product manager, but it is unclear how recently the medical director had clinical experience. No other clinicians appeared to have been involved.	"The CIO was the product owner and the medical director was the domain expert and project manager. They recruited a team of nine employees from the IT department, including three individuals experienced in data science, to conceptualize and develop the cognitive agent" (Reis et al., 2020, p. 285).	Unclear what the output was. Lack of involvement of other domain experts might have contributed to the limited acceptability of the system. Did not explicitly address characteristics of AI.
10. Robodebt	Domain experts were deliberately excluded.	"Centrelink employees who raised red flags before OCI was implemented had their warnings dismissed by the department management: '*Many members stated that concerns were raised during the design process but were simply ignored*'" (Rinta-Kahila et al., 2022, p. 323). "Centrelink did not involve relevant stakeholders, such as DTA, ATO, legal experts, and domain specialists, in the development of OCI. DTA had been 'locked out' from the process, although its involvement could have helped to prevent the problems that emerged later: '*If you are doing silly things like trying to match mis-matching data sets, then we (DTA) would call that out very early in the process'*" (Rinta-Kahila et al., 2022., p. 324).	Excluding domain experts limited the capacity of the developers to see crucial issues, such as the data discrepancy. Not including domain experts limited the ability to address **learning-driven data dependency.**

11. CleverLoan	The ML Provider engaged with Bank employees to better understand the loan decision-making process and practices.	"Specifically, the ML provider engaged closely with the Bank to learn about their practices concerning loan decision-making. They interviewed loan consultants to capture the key criteria applied when making loan decisions. This expert knowledge was used to decide on the variables to be included in the ML model" (Mayer et al., 2024, p. 6710).	This allowed the Provider to gain a detailed understanding of the loan approval process and practices, which informed the development of the model. Did not explicitly address the characteristics of AI.
12. Rayfood	The project leader has a background in child nutrition.	"With a background as a nutritionist and a dietician and heavily involved in child nutrition in schools, they have a passion for nutrition. Changing the habits of children and their families toward healthy nutrition is the main driver of Interviewee 1's quest for innovation. They and their team have over 20 years of experience managing food nutrition programs in the US. They explained that Rayfood Solution's goal is to connect the food supply in the country by bringing the production of datasets on nutrition, waste, and children's choice-making and patterns of meals together. … Background research conducted by Interviewee 1 over 15 years of work in state school districts demonstrated that this inability to provide consistent variety for children often leads to disappointment and disengagement" (Camaréna, 2022, p. 6)	The passion and experience of the project leader influenced the quest for accuracy in the algorithm. Did not explicitly address the characteristics of AI.

Appendix M: Evidence and Outcomes of Encouraging AI and Data Literacy of Users and Other Stakeholders

Table M-1 Evidence and outcomes of Encouraging AI and data literacy of users and other stakeholders

Case	In-house expertise	Evidence	Outcome
1. CAS	[Not really] The intelligence officers were provided with explanations of the techniques used to develop the algorithm, but not detailed descriptions and explanations of how the system worked, despite asking.	"To help the intelligence officers understand the data science practices, the data scientists did explain the techniques they used for developing CAS. For example, they showed the variables that were included in the learning algorithm. Such a list of variables still, however, did not give insight into which variable was considered most important for a given prediction and for what reason, as this was determined by the learning algorithm and unknown even to the data scientists." (Waardenburg et al., 2022, p. 72).	The explanations provided by the data scientists were not sufficient for the intelligence officers; did not allow them to provide the contextualized interpretation required by police managers. "These explanations therefore did not satisfy the intelligence officers' need to understand how the crime predictions were generated and gradually they gave up on their quest to gain deep insights into the practices of the data scientists" (Waardenburg et al., 2022, p. 72). Did not address **inscrutability**.
2. COMPAS	Users were trained on statistics, probability and choosing risk-assessment tools.	"NIC mainly provided assistance by educating the local EBDM teams through workshops and individual coaching… In addition, an agent from the NIC came to Eau Claire and helped the actors with interpreting statistics and choosing risk assessment tools to implement the evidence-based strategy in the local criminal justice system" (Hartmann and Wenzelburger, 2021, p. 277).	Not reported – but respondents seemed confident in using the system.

3. Watson	Deakin assembled a strong in-house cognitive automation team, training SMEs and improving the knowledge of the IT team.	“Thus, the subject matter experts had to be educated on how to write and structure content for inclusion in Watson, which most now do enthusiastically” (Lacity et al., 2018, p. 101).	The multidisciplinary in-house cognitive automation team was important for the success of the project: “Its Watson project team supported all the stages of the organization’s CA journey” (Lacity et al., 2018, p. 102). Addressed **learning-driven data-dependency**.
4. NeuroYou	Training courses on data and statistics were provided by MultiCo to HR professionals.	“However, creating a dataset on which the learning algorithm can be trained is not an easy task for HR professionals and involves new responsibilities. First of all, as discussed above, they are responsible for selecting employees in order to collect the relevant data for training the algorithm. In this process, the HR professionals – as ‘experts’ regarding the employees and the type of work they perform – must make important decisions about the selection of employees and the performance indicators utilized to collect data. Because the selection of employees should represent the organization, this new responsibility for HR professionals also requires new knowledge about data requirements, such as sample selection and data quantity and quality, and an understanding of new data legislation, such as the General Data Protection Regulation (GDPR). To support HR professionals in obtaining this new knowledge, MultiCo facilitates training courses focused on data and statistics. “A consequence of the active role of the HR professionals in gathering data is that in the data analysis phase they are actively involved in discussions about whether or not to include variables that, according to the algorithm, predict success in the organization. In order to align the AI system with MultiCo’s work processes, HR professionals are given the freedom and responsibility to include or exclude certain variables in the AI system of the online games. For	The HR professionals had a direct influence on the variables included in the NeuroYou system, because they understood in part how it worked and what role the different variables might play. Addressed **inscrutability**.

		example, the first results of the AI system show that 'attaching little value to working conditions' can be a significant predictor of a successful employee. According to the HR professionals, this outcome does not fit with MultiCo's work processes, because it could mean that new applicants are selected while they do not care about good working conditions. This type of employee does not match what the HR team considers to be a good employee. In the data analysis phase, the HR professionals therefore decide not to include this variable in the algorithm. As a result of the new responsibilities, the HR professionals thus have a direct influence on the final decision model for selecting applicants." (Waardenburg et al., 2021, p. 54)	
5. ShipCo	Not mentioned – although the paper suggested the Researcher's role would change and she would be responsible for training the algorithm.		
6. Readmission Risk Tool	The developers noticed they needed to explain why thresholds or categories may not be appropriate.	"While refining the tool, it became clear to the developers that the care managers did not fully grasp what kind of data was being collected and how it was being used to generate recommendations. Population Health care managers were also having trouble making sense of the risk scores, since they were used to assessing patients in categorical rather than continuous quantitative terms. A developer said: "'*Instead of using the risk scores, the care managers wanted us to sort patients into red, yellow, and green (to prompt them to follow up with red patients to provide preventative services). Because that's what the care managers are used to seeing (using the prior readmission risk assessment tool)…. We got the care managers to understand that, given the nature of prediction, putting patients into red, yellow, and green categories might make it harder to identify the patients who need the most care*.'	This explanation allowed the end users to better understand the output of the system, and to better use it. Addressed **inscrutability**.

		"Developers addressed this by explaining the risk score: *'We did a crosswalk for care managers where we showed them what is one possible equivalent of red, yellow, green with our model'*" (Singer et al., 2022, p. E29). "'*That helped us persuade the care managers that it did not make sense to look at different groups of patients individually while training the model'* (Readmission Risk Tool Developer)" (Singer et al., 2022, p. E26)	
7. Low Bed Tool	Not mentioned.		
8. Sepsis Watch	[This is training on the tool, not data/AI literacy specifically. Leaving because it is an AI tool.]	"During the first two weeks of the Sepsis Watch pilot, innovation team staff conducted one-on-one training sessions in the hospital to support RRT nurses during shifts" (Sendak et al., 2020b, p. 106). "Moreover, we learned that RRT nurses developed expertise and practices over time that contextualized the information displayed in Sepsis Watch, and facilitated the integration of the tool into existing clinical practice" (Sendak et al., 2020b, p. 106). "Both nurses and physicians were educated on the model's aggregate performance measures relative to other methods, and visualizations of individual patient cases were presented to demonstrate how the model could detect sepsis hours before the clinical diagnosis (Sandhu et al., 2020, p. 3). "Physicians had to learn how to develop, use, and evaluate machine learning models." (Sendak et al., 2020a, p. 11)	Extensive and specific training helped the users understand how the system would work. Addressed **inscrutability**.
9. Anamnesis	Not mentioned.		
10. Robodebt	Not mentioned.		

11. CleverLoan	Self-initiated interest in learning about the system on the part of the Bank.	"Initially, the management of the Bank was particularly interested in the parameters the Provider would use for the ML model to ensure the approach to decision-making aligned with the Bank's values. … Specifically, the Bank's management engaged with their internal IT staff to understand the basics of the ML model and its techniques" (Mayer et al., 2024, p. 6710).	Despite this interest on the part of the client, the developer was not willing to share details, and the results of the Bank's management to understand the basics of ML were not reported. Lack of AI and data literacy training meant **inscrutability** was not addressed.
12. Rayfood	Not mentioned.		

Appendix N: Evidence and Outcomes of Workflow Redesign

Table N-1 Evidence and outcomes of Workflow redesign

Case	Workflow redesign	Evidence	Outcome
1. CAS	The workflow of the intelligence officers needed to be redesigned to contextualize and interpret the output of the AI system for the police managers.	"In the evaluation report, however, the work processes regarding the use of CAS were also critically examined, and it was concluded that steps should be taken to reorganize this, which also required guidelines on how the results of the AI system have to be used. As a result, new responsibilities were formed." (Waardenburg et al., 2021, p. 75)	The new workflow of the intelligence officers influenced what they were able to provide to the police managers. The police managers preferred the interpreted data (to the raw CAS output). Over time, they relied more heavily on the interpreted information from the intelligence officers than on their own intuition. Did not explicitly address characteristics of AI.
2. COMPAS	The introduction of the COMPAS tool meant that practitioners were required to include it in risk assessment before coming before a judge.	"*'The first question the judge is gonna ask us is: 'Was a COMPAS done?' That never happened before'*" (Hartmann and Wenzelburger, 2021, p. 281). "This important impact is palpable in the following exchange with a practitioner on the question of how COMPAS changed the everyday routines of the actors in the Criminal Justice system: '*We were using it (COMPAS) for pre-trial and one way it really helped was on the first offense drug deliveries especially Marihuana. We were able to get those low-risk people on like diversion agreements and deferred agreements as opposed to convicted as felonies; And so that was based on their low-risk*	The tool was integrated into sentencing decisions. Did not explicitly address characteristics of AI.

		COMPAS and that was something we weren't able to do before' (Interviewee)" (Hartmann and Wenzelburger, 2021, p. 281-282).	
3. Watson	Not mentioned		
4. NeuroYou	The decision process to hire a specific candidate changed from an informal discussion to a codification of the decision and the reasons behind it.	"'*There's a big change I have introduced here, which is to write comments in the [NeuroYou] tool. Previously, we only voted yes or no. This time I also ask you to put comments in the tool for two reasons. First, those comments are the most valuable feedback to candidates. Thinking about the candidates' experience, this is the best they can take out of the experience, that our highest leadership has taken the time to give them comments. Another thing that's important is to challenge ourselves about what we need and want from the candidates. The more you put in the comments, the more help you provide me in knowing what you expect from the candidates'*… "Consequently, a key expert hiring practice that involved a lot of social interaction was transformed so the developers could find the categories that played important roles in managers' judgement of candidates" (van den Broek et al., 2021, p. 1572).	Including codification of hiring decisions revealed unexpected patterns in hiring decision-making, such as an anchoring bias. This allowed MultiCo to review its hiring process. Did not explicitly address characteristics of AI.
5. ShipCo	A new role was required to develop the AI system: the data analyst. It was not clear if the analyst role would remain once the system was in operation. The Researcher's role needed to change as a result of the algorithmic system, from manually creating trade tables to training the algorithm.	"As the CDO recognized the need to free up their [the researcher and the data scientist] time, the management decided by early 2019 to hire a new resource within the team. The role of this new resource—called the "data analyst"—was largely to evaluate the algorithmic output and provide the data scientist with information about its performance" (Gronsund & Aanestad, 2020, p. 9). "As the work progressed, the researcher's concerns for her future job had been raised, and the CDO tried to assure her that she would not be replaced: "(The) data scientist's analyses and predictions will be fed back into the system … *'(It) will help you save time on mundane tasks, they will allow you to work more on*	It was not immediately clear in the paper what the outcome of the workflow redesign was for the researcher or for the data analyst. The researcher appeared able to take on new tasks, such as training the algorithm, as a result of the algorithmic system. Did not explicitly address characteristics of AI.

		recent data, and to focus on quality assurance … you will train the robot'" (Gronsund & Aanestad, 2020, p. 9). "His [the CDO] vision was exemplified by the repurposing of the role of the researcher, from manual classification work toward '*training the robot'*") (Gronsund & Aanestad, 2020, p. 9).	
6. Readmission Risk Tool	Not mentioned.		
7. Low Bed Tool	Not mentioned.		
8. Sepsis Watch	The new role and responsibilities for the Sepsis Watch nurse were planned during development; specific tasks and actions emerged during implementation.	"To formalize the RRT nursing workflow, multiple team members met with the Chief Nursing Officer resulting in a subsequent meeting involving nursing leadership from across the hospital. That meeting initiated a month of close collaboration with multiple nursing stakeholders to develop training material, finalize workflow decisions, and better understand staffing requirements" (Sendak et al., 2020b, p. 105). "For instance, RRT nurses developed a practice of working outside of the app and opening a patient's EHR chart before calling the ED physician. By reading through a patient's chart, the RRT nurse was preparing to present the full clinical picture and do "due diligence," in the words of one interviewee, in anticipation of questions received from physicians. This was not a step articulated by the design team prior to implementation, but rather developed as an ad hoc practice that facilitated effective integration" (Sendak et al., 2020b, p. 106). "Clinical stakeholders proposed a workflow in which a specialized team of nurses, known as rapid response team (RRT)	The Sepsis Watch nurses developed their own workflow to manage the interactions with physicians. They reviewed patient charts before calling, they grouped patients, and they engaged in brief small talk to ensure that the physician was available to receive sepsis predictions when they called. They refrained from making diagnoses, and only shared the system prediction. Did not explicitly address characteristics of AI.

		nurses, were the primary end users or Sepsis Watch" (Sendak et al., 2020b, p. 103). "The Sepsis Watch workflow was designed to rapidly identify patients requiring treatment for sepsis…The RRT nurse is instructed to call the ED attending physician to discuss every high risk or septic patient" (Sendak et al., 2020b, p. 103). "Concurrently with model development, an interdisciplinary team of clinicians, administrators, and data scientists designed a workflow to translate outputs from the model into clinical action" (Sandhu et al., 2020, p. 2). "The program required the creation of a new professional <u>Sepsis Watch Nurse</u> role to translate the machine learning algorithm to the patient's bedside" (Sandhu et al., 2020, p. 7).	
9. Anamnesis	Workflow redesign was planned but did not occur because the system was not implemented.	"First, the cognitive agent would engage with the patient and map the conversation to predefined anamnesis schema based on standardized scales and enter the data into the electronic health record (EHR) system….In the second step, the cognitive agent would use robotic process automation to update the patient's EHR information and provide the structured data that the physician needs for diagnosis and treatment. … In the third step, the cognitive agent would analyze the structured data and generate diagnostic and treatment proposals based on patters of symptoms and diseases in labeled anonymized patient data" (Reis et al., 2020, p. 284).	The cognitive agent would have drastically changed the workflow for physicians, but it was not implemented. Did not explicitly address characteristics of AI.
10. Robodebt	The workflow was redesigned to shift responsibilities to the algorithm and remove human oversight from welfare overpayment calculation.	"The new, redesigned process shifted responsibilities for making decisions and performing work tasks from humans to an ADM artefact, resulting in a work system with notably **limited human agency**. … Minimising human oversight entailed full automation of debt-collection processes and put the machine at the centre of the previously human-centred and largely manual process. … The automated system independently estimated welfare overpayments	This new workflow limited human agency of staff, contributing to the negative impact of the Robodebt system.

		and sent debt notification letters to citizens without human scrutiny. There were no longer any checks of accuracy with the recipient or employer) (Rinta-Kahila et al., 2022, p. 322). “Staff were instructed to redirect citizens to the online self-service portal in any debt-notification related matters even if they would have been able to help the citizen over the phone” (Rinta-Kahila et al., 2022, p. 323).	Did not explicitly address characteristics of AI.
11. CleverLoan	The algorithmic system resulted in a new process for approving loans.	“Previously, the consultants were fully in charge of the loan application process. Thus, if “Max Miller” wanted a loan of $10,000 for a new car, he would make an appointment with his consultant, “Tom Smith.” They would meet in Tom’s office and Max would explain his request. Tom would register the application and list the documents Max would need to hand in with his application (e.g., salary statement, confirmation about existing debt, current bank statements). Max would need to apply for some documents from different authorities, so they would agree to meet again within two weeks. At that next meeting, Tom might see from Max’s documents that from time to time he had problems balancing his bank account. However, as Tom has known Max for a long time, he would approve the loan and determine the interest rate and the repayment installments. To complete the application process, Tom would then have to send all the paperwork to a different internal division to have all the details checked. One week later, Tom would have the approval of the internal department and could finalize the loan contract. Once Max signed the contract and after an additional 10-day delay, he would receive the $10,000. “Now, with the CleverLoan AI system, Max makes an appointment to meet with Tom and explains his request. Tom types the data from Max’s identity card into the CleverLoan system and fills in the required fields. He clicks on “Make Request” and, within a few minutes, Tom has the final decision. The AI system decides to grant Max the loan and lists all	The new process is much faster and no longer relies on the consultant’s expertise or human contact with the client. This enabled employees with less experience to become loan consultants. It also impacted the role identity of experienced consultants, who felt a loss of value. It also meant that consultants had more time to engage with customers differently (e.g., cross-selling). Did not explicitly address characteristics of AI.

		conditions, such as interest rate and repayment terms. Tom then goes through the conditions with Max one by one" (Mayer et al., 2020, p. 243).	
12. Rayfood	Not mentioned.		

Appendix O: Evidence and Outcomes of Knowledge Brokers

Table O-1 Evidence and outcomes of Knowledge brokers

Case	Knowledge brokers	Evidence	Outcome
1. CAS	The intelligence officers translated and curated the output of the system to make it usable and actionable for the police managers.	"The direct outcome of the CAS is a map which illustrates − in blocks of 125 m2 in different colours − at which location the chance of a certain type of crime is highest; and a line graph with blocks of four hours for the corresponding times. To ensure that CAS outputs are used in practice, the project team states that these results should reflect '*what officers [themselves] would say*'. This, of course, does not match the map and graph, that still have to be analysed in order to determine where, when and why police action is needed, and what can be done to reduce predicted crime prevalence. The project team therefore gives intelligence officers the task of creating 'ready-to-use' documents by adding contextual information to the results of the AI system. In this way, the results are applicable for police managers and officers. Within the police, this task is referred to as 'enrichment'. "In order to enrich the location and time indications, the intelligence officers make use of the information available in various police databases and general information that anyone could find on the internet. Based on this information, they add more details to the CAS outputs, such as the type of house for which burglary is predicted (for example, 1930s, new construction, student flats). This gives an indication what the reason for burglaries could be, which officers can then anticipate. They also add, for example, which modus operandi is used, or which known suspects often appear at a specified location. Later in this section we provide more insight into the	With time and experience, the intelligence officers relied increasingly on their own interpretations of police data and less on the CAS output. Police managers were happy with the work of the intelligence officers and preferred their curated outputs to the system outputs. They were unaware that the information was curated. Limited ability to address **inscrutability** because a workaround was used, not a true effort to interpret or explain the model.

		possible risks of enriching CAS outcomes by intelligence officers." (Waardenburg et al., 2021, pp. 90-91). "The intelligence officers shielded the police managers from the process through which they generated the substitutes. '*We should keep these choices away from police management*,' said the head of intelligence Rick during one of their department meetings, 'they just need a clear recommendation; we shouldn't bother them with what kind of tools we used for it' (Waardenburg et al., 2022, p. 75).	
2. COMPAS	Not mentioned.		
3. Watson	Not mentioned.		
4. NeuroYou	The people analytics (PA) team was responsible for translating system outputs to make them more relevant to the MultiCo context and more easily interpreted by the hiring managers. One example is the inclusion of visualizations.	"When the HR professionals initially prepared the briefing for hiring managers [with the candidates recommended by the AI system], they used automatically generated visualizations. In doing so, however, two problems arose. First of all, the actual meanings of certain properties in the word cloud (for example, the term 'gregariousness') were generally not clear to hiring managers. These so-called psychometric terms are not used internally in the organization, but fitted the measuring instruments used by the developer. When creating the AI system, the developer was unaware that these terms were likely to be complex and non-intuitive to users. Secondly, it is often unclear to hiring managers whether possessing a certain quality is actually good or bad. For example: is being sensitive a good or bad quality to have as an employee? "In order to eliminate these doubts and ambiguities for hiring managers, and to convey the analytical results more efficiently, the HR professionals asked the PA [people analytics] team to develop tools that simplify the results of the AI system, making them easier to visualize. An example of a new visualization	The visualizations produced by the PA team were appreciated by the hiring managers as they made it easier to understand the AI system outputs. Their insights were also subsequently incorporated into the system by the developers. Addressed **inscrutability.**

		created by the PA team is the spider chart, based on the word cloud mentioned above. … The most important information is prioritized in advance by the HR professionals and the PA team, so managers do not get overwhelmed by an abundance of data. ….” (Waardenburg et al., 2021, pp.96-97).	
5. ShipCo	Not mentioned.		
6. Readmission Risk Tool	Not mentioned.		
7. Low Bed Tool	Not mentioned.		
8. Sepsis Watch	Part of the Sepsis Watch Nurse’s role was to contextualize the output of the AI system and share it with the physicians.	“The program required the creation of a new professional Sepsis Watch Nurse role to translate the machine learning algorithm to the patient’s bedside” (Sandhu et al., 2020, p. 7).	The nurses appreciated this new role, and the physicians and the Sepsis Watch nurse learned to work together. This role helped contextualize the Sepsis Watch output into understandable information for physicians. Addressed **inscrutability.**
9. Anamnesis	Not mentioned.		
10. Robodebt	Not mentioned.		
11. CleverLoan	Not mentioned.		
12. Rayfood	Not mentioned.		

Appendix P: Evidence and Outcomes of Black-Boxing the Technology

Table P-1 Evidence and outcomes of Black-boxing the technology

Case	Black-boxing the tech	Evidence	Outcome
1. CAS	Full details of the algorithm were not shared with the intelligence officers, because developers felt that the algorithm was inherently opaque and too complex to explain.	"[The data scientists] considered algorithmic predictions fundamentally different from police occupational knowledge and were convinced that these predictions could and should be generated away from the police" (Waardenburg et al., 2022, p. 64) "As one of the data scientists explained, 'Intelligence officers don't have to interpret model parameters or any kind of technical stuff; they just get the maps.' The intelligence officers were thus asked to fulfill brokerage work without full insight into how algorithmic predictions were generated" (Waardenburg et al., 2022, p. 67). "However, the data scientists insisted that 'the algorithm did not easily display why something was predicted' (data scientist Jules) and that generating the best predictions required complex techniques for pattern recognition in vast amounts of data, which made the learning algorithm opaque. As a consequence, the data scientists claimed that pattern recognition through machine learning, which combines many different variables and theories, required 'such complex mathematical reasoning that it probably extends beyond human reasoning'" (Waardenburg et al., 2022, p. 72).	The Intelligence officers developed a workaround to be able to interpret the system output and provide usable information to the police managers. Black-boxing the tech in this case did not address **inscrutability** because users developed workarounds without using the system output completely.
2. COMPAS	Not mentioned.		
3. Watson	IBM was not willing to share many details about how	"One interviewee said, 'The challenge for us during the project was trying to get an understanding of what was going on inside	Despite not having complete details about how the system

	Watson worked with the Deakin team.	the black box. We were not invited to technical meetings with the people who understood the machine learning algorithms … we kept asking them to let us into the tent.' … Deakin learned enough about Watson's functional components and architecture to optimize its performance and to provide ongoing support. However, Deakin did not learn how the technology classifies natural language, which was acceptable given the context of student queries" (Lacity et al., 2018, p. 101)	worked, it appears as though Deakin was able to take full advantage of the system. Black-boxing the tech addressed in part the impacts of **inscrutability.**
4. NeuroYou	The opposite seemed to occur: the developer shared the weights and parameters of the model with the client.		
5. ShipCo	Not mentioned		
6. Readmission Risk Tool	Not mentioned.		
7. Low Bed Tool	Not mentioned.		
8. Sepsis Watch	The developers focused on performance and not explainability.	"Model explainability was not prioritized, because regulations promote standardized treatment of sepsis, regardless of cause" (Sendak et al., 2020b, p. 103). "However, in the healthcare context, the urge to transcend the black box is confounded by the fact that in some cases, "the human body is a black box," in the words of a Sepsis Watch team member" (Sendak et al., 2020b, p. 106). "Clinical leaders prioritized positive predictive value as a performance measure and were willing to trade-off model interpretability for performance gains. Model interpretability was low priority because of the many causes of sepsis, and	This did not appear to affect the acceptability of the system too much. Some physicians noted that they did not fully trust the system, in an early study conducted shortly after implementation. However, black-boxing the tech and prioritizing clinical outcomes helped encourage system use. Black-boxing the technology helped address **inscrutability**.

		treatment protocols are largely agnostic to cause" (Sendak et al., 2020a, p. 6).	
9. Anamnesis	Not mentioned.		
10. Robodebt	Not mentioned.		
11. CleverLoan	Developers were increasingly unwilling to share details of how the system worked. Their strategy was to focus on the performance of the system rather than emphasize explainability.	"Whereas in period 1, insights about how the ML model was built and the parameters used for the decision were shared with the Bank, during period 2 the Provider reduced sharing to offering information regarding the loan decision, and the extent to which it was followed by loan consultants in different branches" (Mayer et al., 2024, p. 6712). "'*I can't tell you exactly how our AI system is programmed because this is our competitive advantage, but I can tell you that there is not ONE SINGLE decision-determining criterion*' (CEO, AI Provider)" (Mayer et al., 2020, p. 243). "In this context, the Bank has actively 'blackboxed' the complexity of the ML model by refraining from requesting insights into the model's logic and principles" (Mayer et al., 2024, p. 6714). "The CleverLoan system is transparent, as European law requires, and it does not include neural networks. If the decision is to reject a loan application, the system automatically generates a guideline for explaining the rejection (e.g., insufficient income or excessive debts). However, the guideline does not disclose all reasons for the decision and does not justify specific loan conditions such as the interest rate. In fact, only a few AI Provider managers and employees know the underlying algorithms and the overall statistical model. AI Provier keeps the building blocks of its AI system strictly confidential and does	The client (Bank) had increasingly less understanding of how the model worked, yet the developer focused on performance, and the bank was able to benefit financially from the system. Black-boxing the tech addressed **inscrutability**. Impact on critical thinking was hypothesized but not demonstrated. "From an organizational perspective, both the loss of critical thinking and knowledge outsourcing are extremely troubling in the long term, because employees' awareness is severely impaired or even non-existent. … Moreover, a lack of critical thinking and knowledge of the loan decision-making process makes it impossible for consultants to notice possible errors or factors that could

		not share them with any Main Finance managers or employees" (Mayer et al., 2020, p. 243). "'*The underlying mechanisms of the system are not exactly public. There's a [CleverLoan] score in the background, and therefore it sometimes happens that I have trouble explaining the decision. I can't convincingly explain why it's not possible to grant a loan'.* (Consultant, AID-C, *Main Finance*)" (Strich et al., 2021, p. 317). *"'In our reports, we focused on figure that showed how the default rates have decreased over the last month, quartal etc. And then per branch. And this was what [the Bank] was interested in (Head of AI Provider)"* (Mayer et al., 2024	improve CleverLoan" (Mayer et al., 2020, pp 249-250).
12. Rayfood	Not mentioned.		

Appendix Q: Evidence and Outcomes of Mandating or Encouraging Use

Table Q-1 Mandating or encouraging use

Case	**Mandating or encouraging use**	**Evidence**	**Outcome**
1. CAS	Not mentioned.		
2. COMPAS	Use of COMPAS was highly encouraged but not mandatory	" *'The first question the judge is gonna ask us is: "Was a COMPAS done?" That never happened before. Now, you may say: "Yeah, it was done and here it is," – "Okay, great." Then the judge can look at that. Or if you say "No", you better have a reason to tell the judge why that step wasn't taken'* (Hartmann and Wenzelburger, 2021, p. 281).	The system was widely used. No direct impact on the characteristics of AI.
3. Watson	Not mentioned.		
4. NeuroYou	Not mentioned.		
5. ShipCo	Not mentioned.		
6. Readmission Risk Tool	Not mentioned.		
7. Low Bed Tool	Not mentioned.		
8. Sepsis Watch	Sepsis Watch was integrated into ED operations		
9. Anamnesis	Not mentioned.		

10. Robodebt	Robodebt took over the calculation and collection of welfare overpayment.	“Minimizing human oversight entailed full automation of debt-collection processes and put the machine at the centre of the previously human-centred and largely manual process. … The automated system independently estimated welfare overpayments and sent debt notifications letters to citizens without human scrutiny. There were no longer any checks of accuracy with the recipient or employer” (Rinta-Kahila et al., 2022, p. 332).	Humans were no longer involved in the process. No direct impact on the characteristics of AI.
11. CleverLoan	By the end, the CleverLoan system was mandatory for all loan consultants, regardless of experience	“The third period started in 2017 and is ongoing. During this period, the Bank has fully incorporated the ML outcome as the loan decision (rather than a recommendation). This decision is inscrutable to the Bank’s employees as it determines loan processes in the SLC business area, no longer giving loan consultants the opportunity to ignore or modify the decision” (Mayer et al., 2024).	Loan decisions are fully automated. No direct impact on the characteristics of AI.
12. Rayfood	Not mentioned.		