How can AI implementation within asset management be successfully organized?

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Preface

In front of you is my research: "How can AI implementation within asset management be successfully organized?" This report is written in the context of the master's thesis program in Business Administration - Innovation & Entrepreneurship at Radboud University in Nijmegen. I conducted my master's thesis in collaboration with an internship at Pernino, a consultancy firm in Den Bosch.

I would like to thank my supervisor, Dr. Matthias Weiss, and my mentor at Pernino, Twan van Dijk, for their support throughout the process. Furthermore, I would like to express my gratitude to the respondents for their participation and valuable contributions to my thesis, providing insightful perspectives on AI implementation.

I hope you enjoy reading my master thesis!

Ludo van Bennekom

Nijmegen, August 2023

Abstract

The aim of this study is to investigate how to successfully organize AI implementation in asset management. To date, there has been a lack of research in this area, with previous studies primarily focusing on technological advancements and neglecting organizational aspects. To gather insights, an inductive approach was taken, involving interviews with ten experts in AI implementation within the infrastructure industry. This research is a multiple-case study design, with examining fourteen cases from a total of ten interviews. Using the critical incident technique, the cases were examined were the participants discussed critical incidents from their projects. The findings highlight the importance of end users in AI implementation, as they are the ones who utilize the AI tools and verify data. Successful AI implementation requires organizational adaptation, including an innovation vision, employee composition, and strategy. The fragmented nature of asset management underscores the need for strategic flexibility. Team management, particularly diverse teams incorporating domain knowledge, enhances AI implementation. Successful data management, including long-term and comprehensive data collection, is vital for accurate asset management, necessitating a shift in focus towards data acquisition. Also, the essence of early implementation to gather feedback, ensuring data accuracy and reliability. It also highlights the need for strategic flexibility to address the current fragmented asset structure in asset management. This study contributes to the existing literature by providing a starting point for further research in asset management. The research findings have practical implications for managers in asset management, providing guidance on how to develop their organizations for successful AI implementation. This can assist them in successfully organizing AI implementation in asset management.

Keywords: AI, AI implementation, asset management, organizing AI, infrastructure, innovation

1 Introduction

1.1 Problem description

Artificial Intelligence (AI) is rapidly transforming various organizations, and its potential applications continue to grow. AI has big consequences regarding the policy and management, just as the way of operating in organizations (Agrawal et al., 2019). The reason of the growth of AI is due to the advancing process of digitalisation, which causes interconnectedness between machines, products, services, in addition to the increasing amount of data (Rammer et al., 2022). AI has the ability to interpret and evaluate data, to support in human decision-making, problem solving capabilities and technological innovation (Kaplan & Haenlein, 2019).

Gavrikova et al. (2020) identified strategic asset management as a distinct research category, since then there has been an absence of studies investigating the implementation of AI in conjunction with asset management. Asset management is coordinating activities and practices of the property to let the organization perform as optimal as possible (Ma et al., 2014). The global market size of asset management is 342 billion euro and is expected to grow with 33% per year, with a total global value of 3.457 billion euro in 2030. The large growth is expected, because of the rapid digital changes, like AI (GrandViewResearch, 2023). Asset management is promptly growing in importance as organizations realize the critical role that effective asset management has in achieving strategic goals (Gavrikova et al., 2020). With the increasing complexity of assets, businesses are recognizing that successful asset management can provide a competitive advantage in today's fast-paced marketplace (Al Marzooqi et al., 2019).

Asset management poses challenges due to the inherent limitations of assets, which lack consciousness or awareness. Unlike human resources, assets cannot actively follow management directives or adapt to economic and political changes (Davis, 2016). What sets apart the implementation of AI in asset management is the need for it to align with existing assets. For example, the utilization of cloud computing, which operates online and facilitates the collection of data since the infrastructure itself is also online (Gill et al., 2019). Implementing AI in asset management, such as train tracks, necessitates the use of high-quality data, but obtaining such data presents a challenge. It is not feasible to replace kilometres of train tracks solely to accommodate the latest hardware for data collection purposes since train tracks typically have a lifespan ranging from twenty to fifty years (Patra et al., 2008). Moreover, the risks associated with AI implementation in asset management are substantial, as any missteps could have serious consequences.

With regard to strategy, it must be adapted in response to significant shifts in the technological, competitive, social and legal environment, fostering an environment that encourages innovation (Haveman, 1992). The emergence of AI can be seen as such significant shift that necessitates strategic adaptation within organizations. However, due to the fast development of AI, many organizations

struggle to successfully implement AI and use its full potential for innovation practices (Fountaine et al., 2019). The organizations that achieve success are those that actively learn, refine, and enhance their core competencies, thereby attaining sustainable competitive advantages (March, 1991). There is discussion about the adoption, and the skills and abilities needed to successfully use AI (Mikalef & Gupta, 2021). There are some general factors that are important for AI implementation like: management support and taking into account ethical issues (Merhi, 2023). However, this research focusses specifically on AI implementation in asset management.

1.2 Contribution

Gavrikova et al. (2020) identified strategic asset management as a distinct research category, it also highlighted the need for further research regarding the technological advancements within asset management. Given that cases around asset management are so unique, it can be hard to relate these cases towards other research, see citation about strategic asset management: ‘’The fact that the studies are so different and case-specific makes it hard for practitioners to implement the suggested strategies. […] thus, there is a need to deeper analyse the nature of existing research.’’ Gavrikova et al. (2020, p. 2). When looking at the implementation of AI there is no one size fits all approach, each sector has their own unique perspectives and has unique factors (Füller et al., 2022). Also, when implementing innovation for complex products like AI, it is crucial to carefully navigate the relationship between technology and markets (Tidd & Bessant, 2020). In these scenarios, both technology and markets lack clear definitions and comprehensive understanding, and they mutually evolve as developers and potential users engage in interactions (Tidd & Bessant, 2020). In order to foster innovation, organizations must adapt by realigning their direction, enhancing their capabilities, and addressing the evolving needs of both internal and external customers (Moran & Brightman, 2000).

AI is expected to represent a big technological advancements, impacting how organisations should be organized (Fountaine et al., 2019). AI is expected to have an impact to transform every sector, similar to the effect of the introduction 30 years ago (Bughin et al., 2018). AI was also shown to have significant impact for policy, management, and the operational practices of organizations (Agrawal et al., 2019). The reason of the growth of AI is due to the advancing process of digitalisation, which causes interconnectedness between machines, products, services, in addition to the increasing amount of data (Rammer et al., 2022). It is confirmed that AI has a positive impact on asset management (Ehret & Wirtz, 2017). The question is whether how AI implementation can be successfully organized.

Currently, four papers have explored AI in asset management. The following section provides short descriptions of these four papers. Lu et al. (2020) explores digital twin, a digital replica of physical assets, processes, and systems at city and building levels. It offers insights into the implementation and advancement of digital twin technology. Hernandez et al. (2020) discusses deterioration models based on statistical and machine learning approaches, considering two scenarios: one utilizing only age as an

indicator, and the other incorporating additional available indicators Kumari et al. (2022) discusses a framework for now-casting and forecasting of maintenance of asset management with AI and digitalization. This will be discussed in the theoretical framework of asset management. Alabdulkarim et al. (2015) presents a dynamic model for assessing maintenance systems, simulating predictive maintenance models alongside reactive maintenance. Although the paper is from 2015, it demonstrates the relevance and novelty of the topic, highlighting the need for further investigation into AI, particularly in the field of asset management. To date, research on AI implementation has predominantly focused on general factors rather than specifically addressing asset management (El-Adaileh & Foster, 2019; Kim, 2019; Merhi, 2023).

Considering the emergence of strategic asset management as a separate research category, given its unique cases, which calls for further investigation into the required technological advancements (Gavrikova et al., 2020). The introduction of AI, a technological advancements which is expected to have an impact to transform every sector, similar to the effect of the introduction 30 years ago (Bughin et al., 2018). The fact that AI does not follow a one-size-fits-all approach, as each sector possesses its distinct perspectives and factors (Füller et al., 2022). And that the research that is done about the combination of AI in asset management, which is mentioned above, focusses on the technical aspect of AI. Consequently, this leads to the conclusion that there is a notable gap in the existing research, which limits the derivation of practical insights from current theories. Therefore, this research is done through inductive research, which contributes as a foundational step for future research, providing a starting point for organizing successful AI implementation within the field of asset management.

Given that there is no existing model that encompasses the unique factors of AI implementation in asset management, this study adopts an inductive approach, without using a pre-established model. For instance, the Technology Acceptance Model (TAM), predominantly designed for technology adoption, does not suit the scope of this study, which delves into the implementation of AI (Venkatesh et al., 2003). The key difference between implementation and adoption is that once something is being implemented, the decision to adopt it was already taken, which is why the TAM obviously does not fit here. By using a distinct model, research would be limited to the pre-existing framework. Instead, it focuses on creating a new approach on how the implementation can be successfully organized in asset management.

So, this paper contributes to the literature through a series of propositions grounded in the qualitative data analysis, showing the unique challenges and opportunities inherent on how AI implementation in asset management can be successfully organized. These propositions indicate the complexities and nuances of AI implementation in asset management, serving as a basis for future research. This paper expands the scope of AI implementation research into the domain of asset management, accomplished through an inductive approach that show unique insights of this sector. Moreover, this research

contributes to the technology in this area by highlighting the key improvements needed for successful organizing AI implementation. Through identifying these critical advancements, the paper enriches the understanding of successful organizing AI implementation in asset management.

1.3 Managerial relevance

AI cannot be viewed as a standalone technology that can be easily adopted and integrated into existing business processes. Instead, its implementation requires a transformation in organizational culture, capabilities, and operations (Fountaine et al., 2019). Without proper implementation, AI systems often fail to deliver on their promise (Merhi, 2023). It indicates that 87% of AI and big data projects encounter failure and never reach deployment (Merhi, 2023). When significant projects fail, investigations tend to focus on engineering and technical factors. However, it is often managerial failure rather than technical issues that contribute to project failure (Fountaine et al., 2019; Sauser et al., 2009). Which is further illustrated through the following reference: ‘’90% of the companies that had engaged in successful scaling practices had spent more than half of their analytics budgets on activities that drove adoption, such as workflow redesign, communication and training’’(Fountaine et al., 2019, p. 8).

In asset management, companies are currently investing in technological advancements like, AI, Internet-of-Things, predictive maintenance and more (GrandViewResearch, 2023). The growth of asset management of 33% per year is anticipated through the ability to streamline operations, optimize resource utilization, and ultimately lead to cost savings, increased profits, and improved return on Investment (GrandViewResearch, 2023). Implementing a new technology can pose managerial challenges, as it requires maintaining a positive attitude, grasping its necessity, and guiding the implementation process effectively (Becker, 2010). The findings of this study offer valuable insights for managers in enhancing activities and making informed decisions to successfully organize AI implementation. Enhanced awareness of the implementation factors of AI in asset management given in this research, empowers managers to adeptly navigate the factors outlined by Becker (2010) for the implementation of new technology. Furthermore, these results empower managers to prioritize efforts and allocate resources to critical issues that ensure the successful implementation of AI. By leveraging the findings, managers can enhance the success rate of AI implementation in their organization.

1.4 Problem statement

This research aims to gain insights into the successful organization of AI implementation within asset management. Given the limited existing research on AI implementation in management studies, the objective is to construct a conceptual model through inductive data collection. This leads to the following research question: ‘’How can AI implementation within asset management be successfully organized?’’

1.5 Scope

In order to gain an understanding on how to successfully organize AI implementation in asset management, this research focused on organizations, who recently implemented AI in their organization, relating to asset management. Strategic asset management is of utmost importance for asset-intensive organizations, such as in the infrastructure industry (Gavrikova et al., 2020). The respondents in this study have experience in at least one, preferably two, AI implementation projects within this specific segment. This research is conducted as part of an internship with the consultancy firm Pernino, some respondents may be business partners of Pernino.

1.6 Outline of the thesis

The structure of the thesis is as follows. In chapter 2, the theoretical framework explains the main topics of this research. In chapter 3 the research design and methodological choices are explained. In chapter 4 the results, followed by the discussion, limitations, and future research in chapter 5.

2 Theoretical Framework

2.1 Artificial Intelligence (AI)

2.1.1 AI in general

John McCarthy introduced the term "AI" in 1956 while attempting to develop a way to program robots to perform human actions (McCorduck & Cfe, 2004). The definition of AI: "A system's ability to interpret external data correctly, learn from that data, and utilize those learnings to accomplish specific goals and tasks through flexible adaptation'' (Kaplan & Haenlein, 2019, p. 17). The reference is widely cited in various articles within the management literature (Alsuliman et al., 2020; Bahoo et al., 2023; Bock et al., 2020). The definition highlights the importance of AI within business, achieving specific goals and what the challenge is, interpret (external) data correctly (Kaplan & Haenlein, 2019). The AI definition by Kaplan and Haenlein (2019) is chosen, because it provides the distinction between different types of AI. There are varies kinds of AI: ‘’analytical AI, Human-Inspired AI, and Humanized AI'' (Kaplan & Haenlein, 2019, p. 15). This study is focused on analytical AI, as it pertains to asset management, entailing the measurement, prediction, and analysis of assets, which do not involve emotional and social intelligence. Analytical AI refers to an AI system that learns from past experiences, utilizing them to make informed decisions in the future (Kaplan & Haenlein, 2019). Recognizing the differentiation between an expert system and an AI system is important for this research. An expert system functions based on predefined rules, following the if-then principle, while AI, autonomously learns and extracts knowledge from data (Preece, 2018).

Additionally, with AI three types of learning can be distinguished: supervised, deep and reinforcement learning. Those are defined below.

Supervised learning	a learning technique where a model is trained using labelled data, and its performance is then evaluated on unseen unlabelled data. The process begins by gathering the dataset, then the data is divided into subsets, one being used for training the model, and the other for testing and its learning (Saravanan & Sujatha, 2018).
Deep learning	it involves the exploration of multiple layers of non-linear information processing. Through deep learning a model can learn complex patterns and relationships in data (Kaluarachchi et al., 2021).
Reinforcement learning	It involves learning where the objective is to learn, through a sequence of experiences, where the most optimal actions required to find the best solution. The model interacts with its environment to discover the most favourable solution (Madani et al., 2020).

Table 1 explanation types of learning (Kaluarachchi et al., 2021; Madani et al., 2020; Saravanan & Sujatha, 2018)

2.1.2 Implementation of AI

Organizations are increasingly adopting and implementing AI technologies (Borges et al., 2021). Although the focus of this research lies in asset management, the application of AI within this specific domain has yet to be explored. However, AI implementation research has been carried out in other sectors, such as the hotel industry (Infante-Moro et al., 2021) and agriculture (Talaviya et al., 2020) . In general, the comprehensive examination of crucial factors concerning AI implementation can be classified into four segments, see table 2.

Category	Factors
Organization	‘’top management support, ambiguous strategic vision, organizational culture, organizational structure, and lack of visibility on benefits’’
Process	‘’project champion, resistance, lack of technical expertise, ethics issues and responsibility & accountability’’
Technology	‘’Integration complexity, low data quality, scalable & flexible system, insufficient quantity of data, IT infrastructure, security & confidentiality, and data governance issues’’
Environment	‘’selection of vendors and high cost of AI’’

Table 2 general factors for successful AI implementation (Merhi, 2023, p. 8)

The results suggest that among the four categories, technology takes the foremost position, followed by process, organization, and finally, environment. While ethics issues earn the highest individual score, the overall most substantial score pertains to technology (Merhi, 2023). Considering the distinct nature of asset management, it raises the question whether these factors hold similar importance in the realm of asset management or if there might be distinct factors of importance (Gavrikova et al., 2020). In addition, organizations need to consider security settings when implementing AI, given the swift data processing pace. The level of precautions should escalate with the criticality of a business process to ensure steadfast reliability (Kim, 2019). With this research, the focus being on asset management, this holds particular importance as potential hacking incidents could have far-reaching implications, for example in a country's infrastructure.

2.2 Innovation

2.2.1 General innovation

Innovation can be defined as: ‘’The multi-stage process whereby organizations transform ideas into new/improved products, service or processes, in order to advance, compete and differentiate themselves successfully in their marketplace’’ (Baregheh et al., 2009, p. 1334). The categorization of a product, service, or process as new is subjective and dependent on the perspective of the individuals

involved. When the people engaged in the idea perceive it as new, it is deemed an 'innovation,' irrespective of how others may perceive it as an 'imitation' of something already existing elsewhere (Van de Ven, 1986). Van de Ven (1986, p. 597) illustrates four important concepts when studying innovation: ‘’ideas, people, transactions, and context’’ Transactions refer to the "deals" or exchanges that establish connections between individuals within an institutional framework.

In today's digitalized world, innovation is seen as a process that can be learned. It relies on factors such as human capital, technology, economic considerations, and competitive advantages within corporations (Bahoo et al., 2023; Haefner et al., 2021). The degree of innovation range from incremental to radical, incremental innovations involve minor technological modifications and offer limited customer benefits, while radical innovations, entail the introduction of new technologies and provide significant customer benefits (Chandy & Tellis, 1998).

The process of innovation differs from two to seven phases, depending on the literature (Füller et al., 2022). A popular innovation process is that from Tidd and Bessant (2020, p. 583) illustrate four phases:

1. ‘’Search’’, look for opportunities for innovations, analyse the internal and external environment.
2. ‘’Selecting’’, selecting what is the most suitable thing to do, and why.
3. ‘’Implementing’’, continuing relevant ideas to create new products.
4. ‘’Learning’’, learn from the innovation process and continuously improve the innovation process.

This paper focusses on the implementation of AI, therefore this phase will be further elaborated. Implementing innovation, such as AI requires careful consideration of the interplay between technology and markets. In such cases, both technology and markets are not well defined or understood, and they co-evolve as developers and potential users interact (Tidd & Bessant, 2020). During the implementation, a form of protype is essential to attract users, gain support, from either users within the company as well as investors. Therefore, it is of utmost importance to build functional prototypes, collect user feedback, and analyse it during the process of innovation development (Füller et al., 2022).

2.2.2 Adaptation towards innovation

Innovation requires adaptation through renewing organizations direction, capabilities and taking into account the changing needs of internal and external customers (Moran & Brightman, 2000). Through innovation, change in organizations can happen discontinuously or incrementally (Todnem, 2005). For the continuity of an organization it can better to continuously adapt, to continually monitor and to be able to respond to internal and external developments in the environment (Luecke, 2003). With AI you could argue whether the adaptation towards AI can happen incrementally since it is such a drastic

change (Füller et al., 2022). The environment in which organizations need to adapt to is rapidly changing, especially with AI (Sung & Kim, 2021).

This paper focusses on successful organizing of AI implementation. Success indicates that the goals of the project have been established (Petter et al., 2013). When organizations achieve success over a longer period of time, the natural tendency is to continue exploit the strategy that was so far successful. This is called the paradox of success, which is not limited to individual organizations, but could also be the case on an industry level, where industries do not develop as a whole, due to successes from the past (Audia et al., 2000). Organizations who had success in the past might delay the exploitation of developments of AI, since they were so far successful (Audia et al., 2000).

Shifting from a traditional workspace towards one with AI can be challenging. Organizations take into account the technical requirements of AI, but tend to focus less on the organizational adoption, which needs just as much attention (Fountaine et al., 2019). In order to successfully implement AI, organisations need to make use of cross-functional teams with a mix of perspectives and skills (Fountaine et al., 2019). For example, with maintenance in asset management AI implementation may also involve maintenance workflows which require unique knowledge. So, the implementation needs to involve both the end user as the developer (Fountaine et al., 2019).

Organizations used to make decisions based on past-experience or expertise, AI demands a shift in decision-making (Dwivedi et al., 2021; Füller et al., 2022). It is essential for an AI application to rely on data for optimal performance. By implementing the application at an early stage, it can gather valuable information and leverage its self-learning capabilities to enhance itself (Fountaine et al., 2019). Ultimately, this iterative process of learning and improvement leads to a reduction in failures, thereby increasing the application's effectiveness. An AI application may not have all desired functionalities when introduced, but this can come over time (Fountaine et al., 2019; Merhi, 2023).

2.3 Asset Management

2.3.1 Asset management in general

Asset management is coordinating activities and practices of the property to let the organization perform as optimal as possible. While taking into account the associated performance measures, risks and expenditures through an organizational strategic plan (Ma et al., 2014). Asset management by itself is quite broad, it contains several elements, like: investments, risk management, measuring performance, maintenance and compliance (Van der Lei et al., 2012). The definition of asset is: “Any item of economic value owned by an individual or corporation […] such as buildings, utility infrastructure such as electrical cables, water pipes, rail lines and metro tunnels, and industrial assets such as oil rigs, chemical plants and process plant conveyors’’(Davis, 2016, p. 6). Asset management involves gaining a comprehensive understanding of the life cycle costs associated with infrastructure

and finding ways to extend its lifespan (Davis, 2016). One way to approach is through AI with predictive maintenance.

2.3.2 Maintenance in asset management

The field of predictive maintenance is increasingly incorporating AI, particularly in activities such as equipment condition monitoring and maintenance services (Chen et al., 2021). Maintenance plays a crucial role in asset management as it affects various factors within a system, including downtime, customer satisfaction, product quality, and competitive advantages (Alsyouf, 2006). Achieving a balance between reliability and productivity is paramount in maintenance for asset management (Alsyouf, 2006). However, maintenance is often perceived primarily as a cost centre rather than a source of competitive advantage, despite the significant benefits that can be derived from effective maintenance activities (Gavrikova et al., 2020).

To optimize the effectiveness of asset maintenance activities, intelligent maintenance systems are employed. These systems utilize AI to analyse maintenance operations and identify strategies for minimizing asset downtime (Lee et al., 2020). The efficiency of assets can be enhanced by integrating AI technologies into the decision-making process, potentially replacing, or complementing traditional approaches to asset management (Kumari et al., 2022). This process, known as augmented asset management, involves the provision of a platform that focuses on integrating and transforming data from various sources into valuable information, knowledge, and contextual models. This platform prioritizes domain-specific challenges and adjusts analytics to meet the specific needs of end-users (Kumari et al., 2022).

2.3.3 Strategic asset management

Asset management poses challenges due to the inherent limitations of assets, which lack consciousness or awareness. Unlike human resources, assets cannot actively follow management directives or adapt to economic and political changes (Davis, 2016). However, their condition and performance are affected by how they are handled and utilized, posing a challenge for management (Davis, 2016). Effective asset management plays a crucial role in an organization's strategy, impacting its competitiveness across multiple dimensions. It directly influences costs, flexibility, pricing, quality, production capacity, timely delivery, and environmentally sustainable practices (Al-Najjar, 2007; Gavrikova et al., 2020)

In the realm of strategic asset management, two approaches exist: standardization and individual practices. Standardization is exemplified by ISO 55001, a set of internationally recognized requirements for an asset management system developed by the International Organization for Standardization (ISO) (Godau & Mary McGeoch, 2016). This framework enables organizations to effectively manage their assets throughout their lifecycle, optimize their utilization, enhance generalizability and accomplish their objectives (Gavrikova et al., 2020; Godau & Mary McGeoch,

2016). On the other hand, individual practices and policies vary depending on the specific industry or organization type. Consequently, research findings may pertain to either standardization practices or be applicable only to specific individual practices (Gavrikova et al., 2020). This links to AI implementation, which highlight that there is no one size fits all approach, each industry has its own unique perspectives (Füller et al., 2022).

There is a contractionary regarding long- and short-term planning in strategic asset management. On the corporate level it aims to gain a competitive advantage by managing a portfolio of businesses, on the long term (Thompson, 2008). While operational-level asset management strategy focuses on key activities within functional areas, such as operational planning, asset data management, field staff engagement, service delivery, and short-term implementation of asset management plans (Gavrikova et al., 2020; Mathieu et al., 2017)

2.3.4 AI in asset management

There is a considerable lack of literature in management studies that specifically focuses on the role of AI in asset management. The potential applications of AI for innovation are explained, and how it could potentially relate to asset management. Rammer et al. (2022, p. 3) outline three areas where AI can be leveraged within organizations: ‘’Products, services, and business models […] Innovation process and R&D […] Production, delivery and (maintenance) processes’’. The latter area, production, delivery, and maintenance processes, holds importance in asset management. As AI has the potential to improve multiple facets of the asset management life cycle. This includes performance analysis, forecasting, asset monitoring, predictive and prescriptive maintenance, and supply chain optimization including spare parts management (Mattioli et al., 2020). AI can improve production operations by automating tasks, potentially replacing human labour. Additionally, AI can assist in detecting and preventing maintenance issues, as elaborated in the asset management section (J. Lee et al., 2020).

After conducting the interviews, the type of AI models that are primarily used in asset management became clear. In table 3, are the theoretical explanations of the AI models, which are shown during the cases of the interviews.

Type of AI model	Explanation
Object detection model	A technology that detects objects of a category from snap shots or recordings. As it encounters more examples of objects within images or recordings, it adjusts its internal parameters and algorithms to become more accurate and effective at detecting and categorizing objects of the specified category. This iterative process of learning and adaptation enables the technology to continuously enhance its performance, thus exhibiting a form of autonomous learning, which is a key characteristic of artificial intelligence (Chandana & Ramachandra, 2022).
3D point cloud processing	A data analysis and interpretation technique that deals with three-dimensional sets of points representing the geometric structure of objects in space. Point clouds offer cost-efficient raw data to create the foundation for geospatial digital twins. Through AI, point cloud processing aims to autonomously analyse and interpreting data, providing powerful techniques for handling discrete, irregular, incomplete, and ambiguous data commonly found in 3D point clouds (Döllner, 2020).
Anomaly detection model	Anomaly detection aims at finding unexpected events in data streams, referred to as anomalies. Detecting anomalies serves as valuable insight to uncover novel information and gain a deeper understanding of the data. As the model encounters new data, it updates its understanding of what unnormal events are and adjusts its anomaly detection accordingly. This ongoing learning process allows the model to become more accurate and effective over time in recognizing unexpected events or anomalies within data streams (Schneider & Xhafa, 2022).
Regression model	a statistical method used to estimate and model the relationship between an output variable and the input variables that influences it (Yildiz et al., 2017).
Natural Language Processing	A technique that processes languages, which helps to understand work with human languages. It involves algorithms that can process text created by humans as input as well as generate text that appears natural as output (Bahja, 2020).

Generative design model	A series of technologies is used to solve design problems using AI. It involves seeking a solution to a problem expressed through a mathematical formulation. It involves algorithms to iteratively improve the design optimization process over time. As the model is exposed to more design problems and mathematical formulations, it refines its understanding of optimal solutions and adapts its approach to achieve better results. Through continuous learning from previous design iterations and outcomes, the generative design model becomes increasingly proficient at minimizing objective functions and generating more effective design solutions (Buonamici et al., 2020).
Language model	A model is designed to produce text in various domains such as machine translation, summarization, programming code, and style transfers. Unlike generic models, which focus on specific tasks, language models have a broader use. They can be used for multiple different tasks. Language models are trained on large amounts of text data from the internet and can be further specialized through fine-tuning (Lee et al., 2022).

Table 3 AI model overview in asset management (Buonamici et al., 2020; Chandana & Ramachandra, 2022; Döllner, 2020; Lee et al., 2022; Schneider & Xhafa, 2022; Wu, 2021; Yildiz et al., 2017)

3 Method

3.1 Research design

This study explores how AI can be successfully organized within asset management. AI implementation in asset management is new and has not been extensively researched yet. The existing body of research can be characterized as nascent theory, indicating a scarcity of formal research or theoretical frameworks (Edmondson & McManus, 2007). Considering the limited prior research, an inductive research method is employed. Inductive research facilitates the understanding of how a process unfolds and helps gain insights into a novel phenomenon. An advantage of inductive research is its flexibility, allowing for the discovery of unexpected patterns or relationships (Edmondson & McManus, 2007).

In this research, there is no predetermined theory to be tested. Therefore, the inductive method is utilized for theory building, where the conceptual model is developed based on the collected data. The method used for theory building is Grounded Theory, as defined by Strauss and Corbin (2014), Grounded Theory involves systematically gathering and analysing data in an iterative process, comparing literature, data, and the emerging theory. Furthermore, Gioia et al. (2013) adds to grounded theory the assumption that the organizational world is socially constructed, and that employees have knowledge, enabling them to explain their thoughts, intentions, and actions. The characteristics of grounded theory align with the purpose of this research, which aims to understand how AI can be successfully organized within asset management.

After Gavrikova et al. (2020) identified strategic asset management as a distinct research category, there has been an absence of studies investigating the implementation of AI in conjunction with asset management. Given the complex and rapidly evolving nature of AI in this field, coupled with limited existing literature exploratory research is well-suited to achieve methodological fit (Al Marzooqi et al., 2019). Through exploratory research, researchers can generate novel ideas and insights, uncover patterns and relationships in the data, and develop new theories or models (Edmondson & McManus, 2007). This approach serves as a basis for formulating hypotheses or further exploring research questions related to AI in asset management.

The data collection approach chosen for this study is a qualitative field study involving interviews. Facilitating in the identification of patterns and relationships, through providing a deeper understanding of the complexities of successful organizing AI implementation in asset management (Edmondson & McManus, 2007). Interviews are particularly valuable for theory-building, as they allow for the exploration of complex and dynamic phenomena within real-world contexts (Gioia et al., 2013). Comparing interviews to other research methods, like surveys or experiments. Interviews are beneficial for this research as they allow for more flexibility and create a deeper understanding of the

phenomena. This context is yet new, so a degree of flexibility is essential to be able to adapt during the data collection (Gioia et al., 2013).

3.2 Data source & collection

In this context, the unit of analysis are the AI implementation projects in asset management. These projects involve a range of activities, decisions, and processes focused on the implementation of AI in asset management. Each discussed project represents a distinct case with its own challenges and objectives, all these cases are evaluated, providing new insights in the context of AI implementation in asset management. The examination extends from the initial introduction of AI concepts through the developmental stages, culminating into the integration into asset management practices. Each individual project serves as a distinct case, characterized by its unique objectives, challenges, and outcomes. By delving into these projects, novel insights emerge that contribute to a comprehensive understanding of AI implementation within asset management. To ensure a focused analysis, this study focussed on a specific industry of the asset management landscape: the infrastructure industry. This focus facilitates a better comparative evaluation of AI implementation outcomes. The infrastructure industry is selected for analysis due to the substantial importance of assets within this industry (Gavrikova et al., 2020).

Given the newness of AI in asset management, there is limited experience of people who have experienced AI implementation in this sector. Informants need to have experience with at least one, preferably two projects with AI. The informants selected for this study are considered experts in the field. Their expertise stems from their direct involvement and experience in AI implementation projects within asset management. Because the informants have actively participated in and overseen the implementation of AI, they possess valuable insights and first-hand knowledge about the complexities and challenges of successful AI implementation. Drawing upon the insights of Gioia et al. (2013), who emphasize the socially constructed nature of the organizational world, employees are seem to be as knowledgeable, enabling them to explain their thoughts, intentions and actions to provide valuable insights for this research. Given this, these experts contribute a rich understanding of AI implementation in asset management.

The selection of participants to this study was done through purposeful sampling, which means that the researcher selected participants based on their own judgement of suitability (Palinkas et al., 2015). This master thesis is combined as an internship at Pernino, so the network of the consultants of Pernino can be used to get access to those organizations. Additionally, employees of large infrastructure organizations were contacted through LinkedIn, if they were willing to participate for this research, or if they could recommend me towards other potential informants. When participants were found, snowball sampling was used to recruit and recommend more participants (Goodman, 1961).

Before interviewing, informants were asked questions, to introduce the AI project, and meant as a preparation for the interviewer. These questions can be found in Appendix 6.1. The interviews were then collected through Teams. The respondents were all from different projects, given AI in asset management is still so new, getting as much different insights can be important to gain different perspectives. Additionally, that is also why each respondent was asked to discuss two projects to increase the variety of insights.

This study interviewed ten experts with experience in AI implementation in asset management infrastructure. The characteristics like job title, kind of company, number of employees and number of discussed cases can be viewed in table 4, next page. Regarding the interviews, informants were interviewed using semi-structured open-ended interviews, questions to let the participant and interviewer expand on the answers and questions (Blijenbergh, 2013). Since this is an inductive research, the questions are not derived from a theoretical framework, but rather by the critical incident technique. This approach involves examining significant events, processes, or issues from the respondent perspective (Gremler, 2004). The critical incident technique is useful for theory development, which is particularly interesting for this research, giving its inductive approach (Gremler, 2004). The interview questions are listed in appendix 6.2.

The critical incidents pertain two projects, one successful project as well as a less successful project. An event can be classified as a ‘’critical incident’’ if it significantly contributes to the objective of the activity and is open to critique or analysis (Gremler, 2004). The aim is to gain a comprehensive understanding of the event. This interview technique focusses on exploring the reasons and methods behind something, leading to the derivation of theories. It is crucial to consider the respondent’s perspective, including their emotions, feelings and thoughts (Gremler, 2004). Towards the end of the interview, respondents were also asked general topics related to AI implementation, if they had not been talking about that during the cases. These questions are also visible in appendix 6.2.

Respondent number	Job title	Company	Number of employees	Number of cases discussed
1	Product owner image recognition	Government-related organization	1001 - 5000	2
2	Business consultant asset management	Construction organization	10.000+	2
3	CEO	Consultancy for AI in asset management	11 – 50	1
4 - Two persons	Scrum master, Program manager	Government-related organization	10.000+	1
5	Digital information manager	Construction organization	501 - 1000	2
6	Project- and asset manager	Construction organization * same as R2	10.000+	1
7	Advisor digital manager	Advisory firm	1001 – 5000	1
8	Innovation manager AI	Advisory firm	51 - 200	1
9	Technology & Innovation manager	Water purification company	1001 - 5000	2
10	Business analyst	Consultancy for AI in asset management	11 - 50	1

Table 4 respondent characteristics

Finally, after initiating the data collection process, adjustments were made to the initial approach. It allows for the refinement and validation of the emerging theory in grounded theory as data collection and analysis progress (Edmondson & McManus, 2007; Strauss & Corbin, 2014). The initial respondents primarily consisted of experts in the technical aspects of AI. However, considering the research focusses on successful organizing AI implementation, the scope was expanded to include managers with greater experience in the business aspect of AI implementation, such as innovation manager. It was essential for these managers to also possess technical knowledge of AI, which narrowed down the pool of potential informants. Nonetheless, a sufficient number of respondents were eventually collected. Furthermore, slight modifications were made to the initial questions to better align them with the research question. The original questions placed excessive emphasis on the technical aspect of AI implementation. The revised questions can be found in appendix 6.3.

3.3 Operationalization

It is important to operationalise the concepts for this research. The concepts are elaborated in the theoretical framework, but further explained here.

Kind of model

The type of AI model used in each case is determined, and a description of each AI model can be found in 2.3.4 AI in asset management.

Learning

The type of learning used in each case is determined, and a description of each type of learning can be found in 2.1.1. AI in general.

Measuring success

Success indicates that the goals of the project have been established (Petter et al., 2013). The success of the implementation of AI is measured through Jansen-Vullers et al. (2008), who measured the impact of performance of the redesign of a business process. The cases that are discussed during the interviews are all processes that are redesigned through AI. However, because these measures are not taken into account when designing the research questions the performance measures, are changed towards the available information. The success of AI implementation is measured based on the four principles: time, cost, quality internal and quality external. A case is considered successful for this research if it scores high on all four principles, somewhat successful if it scores low on one of the four principles, and unsuccessful if it scores low on two or more principles.

1. Time dimension:
    a. Is the project handled within the given time? (changed)

Since the operationalisation was added afterwards the original measuring of success of time based of Jansen-Vullers et al. (2008) cannot be taken into account, which is lead time, time it takes to handle an entire case. Instead, the total time of the project is taken as a measured and whether the project is completed within the given time.

2. Cost dimension
    a. Is the project actually cost effective? (changed)

The cost dimension is also changed, because the original measurement was the original measurement was on various costs like labour, transport, and resource costs. Instead, the focus is towards whether the total project is actually cost effective.

3. Quality internal
    a. The work has a substantial impact on the lives or work of the employees.

b. direct and clear feedback about performance effectiveness is available.

4. Quality external (if it involves a client)
    a. The degree to which the customer feels satisfaction with the delivered product.

3.4 Data analysis

The semi-structured interviews are audio-recorded with consent of the respondents. The interviews are transcribed to textual data according to the verbatim transcription, which implies that the written words are an exact replication of the recorded words (Blijenbergh, 2013). Drawing upon grounded theory as the analytical approach, the data analysis process involved several key steps. First, the transcripts are carefully reviewed and coded, which entails systematically identifying and labelling meaningful units of information within the data. Codes capture the essence of participants' statements or concepts relevant to the research topic. (Strauss & Corbin, 2014). The coding process contains of open, axial and then selective coding, Gioia calls this 1st order, 2nd order and aggregate dimensions (Gioia et al., 2013; Strauss & Corbin, 2014). It is important to stay relatively close to the words used by the respondents in the initial round of coding. In the second stage, the 2nd order themes, similarities and differences among the codes are examined. Through constant comparison and refinement of these categories, connections, and relationships between them emerged. In the aggregate dimensions, the focus was on identifying themes that may be explained by theoretical information. However, the emphasis is on nascent concepts that lack sufficient theoretical references or existing concepts that are new to another domain (Gioia et al., 2013).

3.5 Research Ethics

For this research, the research ethics has been taken into account by having the following procedures. Firstly, respondents were asked permission to record them, the recordings are handled with great care, and the recordings will be deleted after the research. Secondly, the names of the informants are not included in the research. Thirdly, the respondents will be informed of the results of the research. Fourthly, participating in this research is completely voluntary, and informants can withdraw from the research at all times. Lastly, it is crucial to create a comfortable environment during the interviews, ensuring that no questions cause any harm to the participants, such as the disclosure of confidential information.

4 Results

This chapter is divided into four sections. The initial section presents an overview of the cases. Secondly, there is an outline of the data structure according to Gioia et al. (2013) of grounded theory, illustrated in figure 1. This is followed by extensive explanations of the dimensions, including quotes, wherein each 2nd order concept is associated with a proposition. Lastly, the presentation of the conceptual model.

4.1 Overview cases

Table 5 and 6 present an outline of the cases extracted from the respondent interviews. A more in-depth explanation of each case can be found in Appendix 6.5. The factors are derived from the from the operationalization, discussed in the previous chapter.

Aspects	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Respondent	1	1	2	2	3	4 (2 people)	5
Job Title	Product owner image recognition	Product owner image recognition	Business consultant asset management	Business consultant asset management	CEO	Scrum master, program manager	Digital information manager
Type organization	Government related	Government related	Construction	Construction	Consultancy for AI in asset management	Government related	Construction
Kind of model	Object detection	Object detection	3D point cloud processing	3D point cloud processing	Anomaly detection	Regression model	Natural language Processing
Learning	Supervised learning	Supervised learning	Deep learning	Deep learning	Deep learning	Supervised learning	Supervised learning
Degree of being used	Integrated	Integrated	Integrated	Integrated	Integrated	Integrated	Integrated
Measuring success:	Successful	Unsuccessful	Successful	Somewhat successful	Successful	Successful	Successful
1. Time within given time:	Yes	No	Yes	No	Yes	Yes	Yes
2. Cost effective:	Yes	No	Yes	No	Yes	Yes	No
3. Quality Internal: Impact / feedback	High / high	Medium / Low	High / medium	High / medium	Not clear	Medium / high	High / high
4. Quality external	Not the case	Not the case	Satisfied	Satisfied	Satisfied	Not the case	Not the case
Short information	Detecting damages on assets based on video recognition	Detecting type of assets based on video recognition	Making a digital twin of infrastructure detecting damages	Making a digital twin of infrastructure detecting damages	Predicting malfunction of assets based on energy use	Predicting whether an asset needed cooling	Summarizing information from various sources for mechanics

Table 5 case overview 1/2, further information about the cases can be found in Appendix 6.5 case description

	Case 8	Case 9	Case 10	Case 11	Case 12	Case 13	Case 14
Respondent	5	6	7	8	9	9	10
Job Title	Digital information manager	Project- and asset manager	Advisor digital manager	Innovation manager AI	Technology & Innovation manager	Technology & Innovation manager	Business analyst
Type organization	Construction	Construction Same as Resp. 2	Advisory	Advisory	Water purification	Water purification	Consultancy for AI in asset management
Kind of model	Regression model	3D point cloud processing	Generative design model	Language Model	Predictive model	Object detection model	Object detection
Learning	Supervised learning	Deep learning	Reinforcement learning	Supervised / reinforcement learning	Supervised / reinforcement learning	Supervised learning	Supervised learning
Degree of being used	Failed pilot	Integrated	Pilot	Pilot	Integrated	Pilot	Integrated
Measuring success:	Unsuccessful	Successful	Somewhat successful	successful	Successful	Somewhat successful	Successful
1. Time within given time:	no	Yes	Not clear	Yes	Yes	Yes	Yes
2. Cost effective:	No	Yes	Pilot	Pilot	Yes	No	Yes
3. Quality Internal: Impact / feedback	Low / medium	high / high	Medium / medium	High / medium	Medium / high	Medium / medium	medium / high
4. Quality external	Not the case	Satisfied	Satisfied	Not the case	Not the case	Satisfied	Satisfied
Short information	Predicting when the lifecycle of an asset ends	Making a digital twin of infrastructure detecting damages	Designing an asset based on parameters	Designing own ChatGPT for internal use	Aid in water purification, identify toxic emissions	Counting animals through drone shots	Detecting damages assets through video

Table 6 case overview 2/2

4.2 Data structure

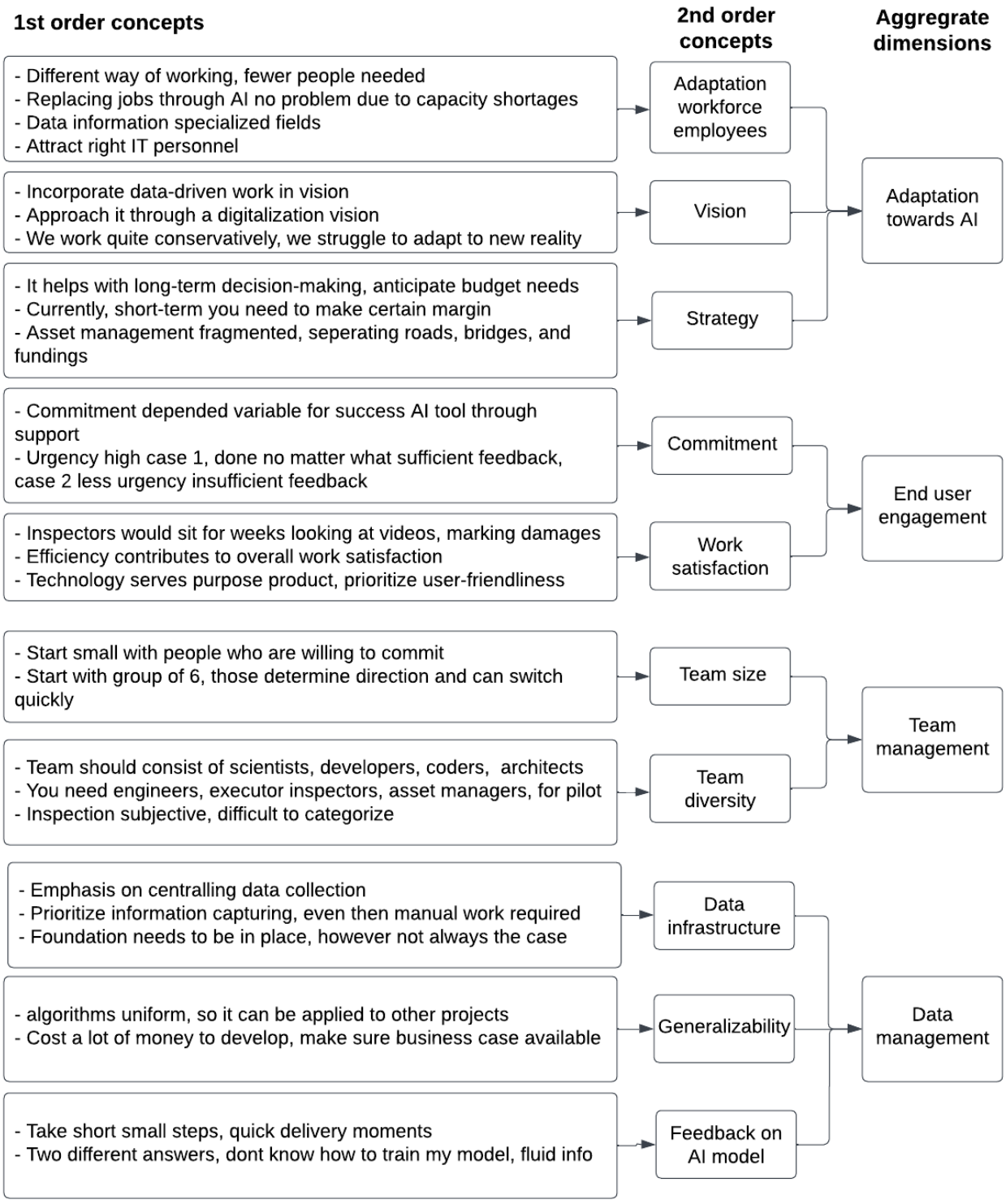

Figure 1 data structure

4.3 Adaptation towards AI

While AI in asset management is still in its early phase of development, noticeable changes are already taking place. As this technology continues to evolve, further transformations are anticipated. In the following paragraphs is referred to quotes of the respondents, these can be found in Appendix 6.4.

4.3.1 Adaptation workforce of employees

For successful AI implementation, adaptation in the workforce of the employees is required. In previous asset management workforces, numerous inspectors were required to manually assess assets, like damages. However, through the development of AI, these tasks can now be handled by an AI model. As a result, there has been a shift in the roles of employees, as the responsibility of who is evaluating assets changes. This was reliant on manual labour, now could be taken over by AI-tools, see illustration where R10 talks about how AI adapts the way of working, **R10(case14):** ‘’That is simply a completely different way of working. It allows inspections to be carried out with fewer people.’’ This minimizes the need for manual inspection and transform the tasks of the employees. The reduced work is not seen as a problem, as AI has the potential to reduce workloads and addresses labour shortages in asset management, see quote1(case 9) (appendix 6.4). It is seen as a solution rather than a threat, as the scarcity of available workers changes perceptions. However, with fewer inspectors needed, the remaining workforce needs to adapt to the new way of working and requires more knowledge about AI.

Employees who are currently involved in implementing AI in asset management like: project leaders, contract managers and asset managers often lack knowledge how to handle data and use AI, see quote2(case 8). It emphasizes that data and information management are specialized fields, not something to be taken lightly. They observe that some individuals in project and asset management roles may mistakenly believe that having access to data is like possessing a magic solution. However, the reality is more complex and requires a better understanding of data and information management, including its possibilities and limitations.

In order to successfully implement AI, organizations need to recruit AI-knowledgeable IT specialists. Hiring new employees proficient in AI may be necessary due to the lack of expertise in the existing workforce. However, attracting these skilled professionals is challenging as asset management, may not be perceived as appealing to work, **R6 (case9):** ‘’you want to attract the right IT personnel to your company, right? […]. So, it's quite a challenge for an organization to attract and retain people, as well as keep them engaged and facilitate their ongoing development.’’ Important to note that the respondents only discussed the recruitment of IT specialists with expertise in AI, rather than focusing on the process of training employees. Furthermore, considering the necessity of domain knowledge for AI implementation in asset management, see quote7(case 9), the option of internally training individuals could be explored, however this aspect was not specifically addressed in the interviews.

So, AI has the potential to transform the workforce asset management, reducing the need for manual labour. This shift will change employee roles and address labour shortages. However, the remaining workforce may lack knowledge of AI system capabilities. Additionally, data and information management are specialized fields that require a deeper understanding. In order to successfully organize AI implementation in asset management organizations need to focus on attracting IT personnel with AI knowledge.

Proposition1: Adapting the workforce by attracting new IT specialists who possess additional knowledge about AI positively influences successful AI implementation in asset management.

4.3.2 Vision

In order to successfully organize the implementation of AI, an organization must embrace a new approach of working. To make this shift, it's crucial for the organization's vision to be clear, emphasizing the significance of AI or even broader, innovation, as essential values within the company, see **R2(case4)**:‘’incorporate it into vision and strategy. In our case, data-driven work is one of the key strategic pillars. But, it's about innovation in general, being open to new techniques and innovations. […] it encourages your team to be more receptive’’ The organization prioritizes data-driven work, embraces innovation, new technologies, and innovative practices to align their vision with AI and foster an innovation environment. They emphasize the importance of incorporating innovation for easier adoption of new technologies, like AI which is shown not only through them, but also to partner companies. Through emphasizing data-driven work and innovation in the vision it is expected to boost adaptation. By adopting such a vision, organizations can stay ahead of the curve and successfully leverage innovation in their business practices, aligning with the organization's focus on leveraging data and AI to keep up with digitalization in asset management.

Comparing R2's vision, which is focused on data-driven approaches, towards R8's vision that does not incorporate innovation or data-driven work in their vision. This comparison shows difficulties in successfully organizing AI implementation with a lacking vision, see **R8(case11):**‘’We are an organization that works quite conservatively. […] However, they struggle to adapt to the new reality. […] the implementation of any kind of technology, especially AI, within an organization requires change.‘’ For employees to adapt towards the new way of working, the company's vision must align with upcoming innovations. To keep pace with the latest innovations, an organization must align its vision to drive change. An innovative vision is beneficial AI implementation as it facilitates change, embraces new technologies, and provides clarity on future goals. In asset management the focus tends to be more short term, with innovation, especially with AI it requires a more long-term approach allowing to make an investment which can later be beneficial, see **R6(case6):**‘’That's all quite short-term. So, every year you need a certain margin at the bottom line, otherwise your company will eventually not do well. However, these kinds of developments require a long-term vision and long-

term investment.'' While organizations acknowledge the importance of innovation and data-driven work, there may be a lack of actual adoption and integration of AI technologies. It emphasizes the need for a proactive approach in understanding and leveraging the potential benefits of AI through a clear vision.

Proposition2: a vision that prioritizes data-driven work and fosters innovation, boosts adaptation, which positively influences successful AI implementation in asset management.

4.3.3 Strategy

In order to successfully organize AI implementation, an organization needs to adapt its current strategy towards a more open flexible strategy. In asset management, the existing strategy is often divided assets among various units, assigning distinct responsibilities for specific assets. Instead of this fragmented approach, emphasizing overall innovation, through a more combined strategy allows organizations to foster innovation across their entire spectrum and domains through various assets, see **R7(case10):**''The approach revolves who is responsible for the: roads, bridges, public lighting, and so on. There are separate funding sources, budgets, often fragmented organizational structures surrounding these areas. The focus is on managing budgets and the performance of specific assets.''

This fragmentation within asset management presents challenges when attempting to initiate AI implementation projects. The process of gathering funding and constructing a business case for AI can be complicated by the existing fragmented strategy. The division of assets across various units may lead to difficulties in gathering financial resources and acquiring the necessary information and support for AI initiatives given each department has its own budgets. In addition, managing individual assets hinder the realization of broader innovation opportunities. Innovations tend to be concentrated on enhancing the performance of specific categories of assets, often overlooking the potential for cross-domain application. To address this limitation, the strategy needs to be adapted, emphasizing a more flexible strategy without a narrow focus on specific categories of assets. This enables organizations in a more flexible approach and potentially makes it easier to acquire budget and potential cross-domain application. By adopting a more holistic perspective, organizations can channel innovation efforts across various domains, leveraging the expertise and resources available within the organization to drive AI implementation more successfully. Each category is accompanied by distinct funding streams, budgets, and organizational hierarchies. Instead, the emphasis is placed on fostering innovation across all asset domains, promoting collaboration and resource-sharing to successfully AI implementation.

Proposition3: Embracing a flexible strategy, positive influences successful AI implementation in asset management.

4.4 End user engagement

Nearly all respondents acknowledged the importance of end user feedback in their AI implementation process, see **R5(case7):**‘’Take the end user along, that's the most crucial point that I carry with me throughout software implementation overall. Don't think you can think on their behalf because you simply can't.’’

4.4.1 Commitment

The end user’s commitment includes providing necessary feedback throughout the implementation process, ensuring that the product meets their needs. The continuous feedback shows active involvement and dedication among the end user. The commitment of the end user enhances the success by meeting the requirements of the AI-tool and that of the end user. **R1** discussed two cases: one successful and one somewhat successful, they attributed that the main difference in success was to the varying levels of urgency, see quote3(case1&2). In case1, with high urgency and a clear goal to finish the task within the year, users were motivated to actively use the tool, identify areas for improvement, and address them. In contrast, case2 had less urgency and time-consuming output processing, resulting in limited feedback. Consequently, the tool could not improve its performance or achieve successful outcomes due to the lack of necessary input, **R1(case2):**‘’Eventually, it all depends on how you prioritize things, and that is truly a management task to set the right priorities.’’ To successfully implement AI in asset management, gathering sufficient feedback from the end user is crucial. The builders of the AI tool may have different backgrounds and perspectives, so it's important to ensure that the tool is understandable for the end user to acquire feedback.

Proposition4: Creating commitment increases feedback amongst end users which positively influences AI implementation in asset management.

4.4.2 Work satisfaction

The shift from traditional working methods to working with AI tools often relieves the end user from having to deal with large amounts of data directly, **R6(case9):**´´various inspectors would sit there, well, for weeks, watching those video recordings on a screen and individually marking the damage in the images.’’ The support of an AI tool to make sense of this data notably enhances work satisfaction for employees. During the implementation process, it is essential to show the end user the tangible results produced by such an AI tool. If the AI tool performs tasks that are typically unfavourable, the end user is more motivated to provide necessary feedback for valuable input. The user friendliness of the system may hold equal importance as to the technology itself, as the tools success depends on the user’s ability to comprehensively use the AI-tool, see quotes 4(case8) and 5(case14). Work satisfaction plays a crucial role in driving AI adoption, particularly in the initial stages of AI implementation.

Proposition5: Enhancing work satisfaction of the end user positively influences AI implementation success in asset management, through increased end user engagement.

4.5 Team management

As asset management undergoes digitalization, team management practices are expected to evolve and adapt to leverage the full potential of AI, **R9(case12):‘’**It's just the very beginning. We're working on AI with a few people in a company of 1800 employees, in 10 years it will be really different.’’

4.5.1 Team size

Since the development of AI is just starting within asset management teams need to communicate a lot to further develop and implement AI. Effective communication among teams is necessary for further development and successful implementation. Working with a smaller team size helps in terms of fast decision-making and adaptation. This also allows for teams to respond fast to the evolving environment and challenges associated with AI technologies in asset management, see quote6(case11), it states six people is the ideal team size and **R6(case9): ‘’**You need to start small with people who are willing to commit, both in the operations and projects, as well as with the customers and IT personnel. Put them all together in a group or team.’’ So, a smaller team size makes it easier to adopt to changes, enables efficient communication, faster decision-making, more effective communication. However, the implementation projects within asset management are still in the early stages of adoption, so the team size may vary when the projects differ in complexity, context, or available sources.

Proposition6: A smaller team size, positively influences successful AI implementation in asset management.

4.5.2 Team diversity

In addition to team size, team diversity is also importance in team management to successfully organize AI implementation in asset management. The diversity is necessary for diverse knowledge of the various important elements within AI implementation, **R8(case11):**‘’The team should consist of data scientists, IT developers, coders, and IT architects. Furthermore, a manager should be appointed to oversee the team's operations and ensure effective coordination and communication.’’ Successful team diversity in AI implementation involves the collaboration of data scientists, AI specialists and domain experts, even though a small team size is preferred for effective communication. Including at least one domain expert in the project team is advantageous for AI implementation. The integration of domain experts and technical specialists, through collaboration with IT professionals, proves beneficial in successfully implementing AI in asset management, see **R6(case9)**: ‘’Including a: maintenance engineer, executor, inspector, asset manager. […] At least one of these should be included in the team to initiate a pilot project […] This is one of the key success factors in implementing AI in asset management.’’ Incorporating domain experts into the team brings valuable domain knowledge specific to asset management. This knowledge provides a deeper understanding of

the context and challenges associated with AI implementation in this field. It is worth noting that domain knowledge can introduce subjectivity, as mentioned in quote8(case14). Successfully managing this subjective knowledge in data management can be challenging AI implementation in asset management.

Proposition7: Involving at least one domain expert in a team positively influences successful AI implementation in asset management.

4.6 Data management

AI implementation relies on extensive data utilization, posing challenges due to its complexity.

4.6.1 Data infrastructure

To succeed with AI implementation, a key factor is establishing a solid data foundation, which involves high quality data collection, see **R9:**‘’The foundation must be in place. […]. However, this is not the case for all companies. Often, you need to extract data from somewhere else, conducting local analysis or other methods, and then implementing it.’’ The data infrastructure in asset management is often a lacking factor which hinders the successful implementation of AI. Extracting data from various sources, conducting analysis and implementation solutions can be challenging if the database and infrastructure is limited or lacks stability. Also, a shift from immediate outcome to long-term value, which was also seen in vision is necessary. Asset management practices, tend to prioritize delivering a report and considering the task complete. However, for successful AI implementation focusing on data, which may involve gathering data for multiple reports is essential, see quote9(case 14). Data infrastructure in asset management is also somewhat unique because an AI model needs to take into account various situations like weather, region, seasons over a course of multiple years to train the model, see quote10(case13), quote11(case2) and illustration **R9(case13):**‘’Ideally, you would have data from multiple years. It is different from conducting an AB test and having your results after two weeks, knowing, this is the best thing to do."

In achieving successful AI implementation, a shift is essential, moving away from prioritizing the end result and instead emphasizing the centralization of data collection. This necessitates a focus in organizing the data infrastructure within the organization. It is important for organizations to prioritize data management and ensure that data is readily available and up to date, collected at all times. This may involve changing manual work requirements and streamlining data collection processes. Organizations need to place a high priority on data management, ensuring the availability and currency of data through continuous and consistent collection efforts. This has consequences for an organization through revising manual work procedures in order to optimize data collection workflows.

Proposition8: Establishing robust data foundation enhances successful AI implementation in asset management.

4.6.2 Generalizability

The realm of AI in asset management is still in its early developmental phases. Within this process, prioritizing the generalizability of both data and models is of paramount importance. This entails ensuring adaptability of models to diverse contexts and focusing on versatile data. By placing an emphasis on generalizability, organizations can unleash the full potential of AI implementation in asset management, see illustrations **R2(case3)**:‘’It is important that we have made the data or algorithms as uniform as possible so that it can be applied to any projects.’’ Additionally, **R6(case4)**:’’ it is important, to look where the business case actually lies. And if you can spread it across multiple projects as well." This standardization supports that models can transition and find utility across different scenarios, consequently enhancing their generalizability. This comprehensive approach not only ensures the versatility of models across projects but also aligns with the cross-domain application, as mentioned with strategy. Incorporating considerations for the business case further optimizes cost-effectiveness, feasibility, and the widespread application of the tool, see quotes 12(case12) and 13(case9). Ultimately, the generalizability involves the establishment of standardized data and algorithms, perpetuating their continual reuse, and tactically evaluating the business case. By taking these factors into account, organizations can successfully implement AI.

Proposition9: Generalizability in AI models positively influences successful AI implementation in asset management.

4.6.3 Feedback on AI model

The paragraph on end user engagement underscored the importance of feedback for successful AI implementation. Moreover, feedback holds importance in ensuring successful data management. In the process of soliciting feedback, the incremental approach proves pivotal, eliciting input and promptly integrating it. Organizations can proactively elicit feedback from end users by subdividing the implementation into manageable segments. This approach facilitates testing and feedback collection for each facet of the AI model, with the gathered insights seamlessly integrated into ongoing development. This iterative process, is exemplified by **R9(case6):**"There are many small steps involved, and the key to success is taking those small steps each time and implementing them right from the beginning." And **R6(case9)**: ‘’It's about taking, small steps. Try to have quick delivery moments for part of the product and immediately test it. Then, take any feedback from that testing and incorporate it to keep developing it."

Acknowledging the subjective nature of data is imperative when considering feedback, particularly as it can sometimes introduce bottlenecks in data collection. For instance, when identifying diverse types of asphalt cracks, discrepancies may arise between assessments from different road inspectors. This inherent subjectivity poses challenges during model training, see quote8(case14) and **R10(case14):**’’I can't work with that I get two different answers, I don't know how to train my model. it's funny to

realize how fluid it is, how much subjectivity is involved in something like a road inspection.'' The subjective nature of road inspections highlights the need for feedback for AI models in asset management. Within the implementation of AI, feedback assumes a critical role, necessitating a gradual and incremental approach to ensure data accuracy and the proper functioning of the model.

Proposition10: Feedback on the AI model enhances data management, which positively influences successful AI implementation in asset management.

4.7 Conceptual model

Finally, through discussing concepts in the previous paragraphs the following conceptual model is conducted, see Figure 2.

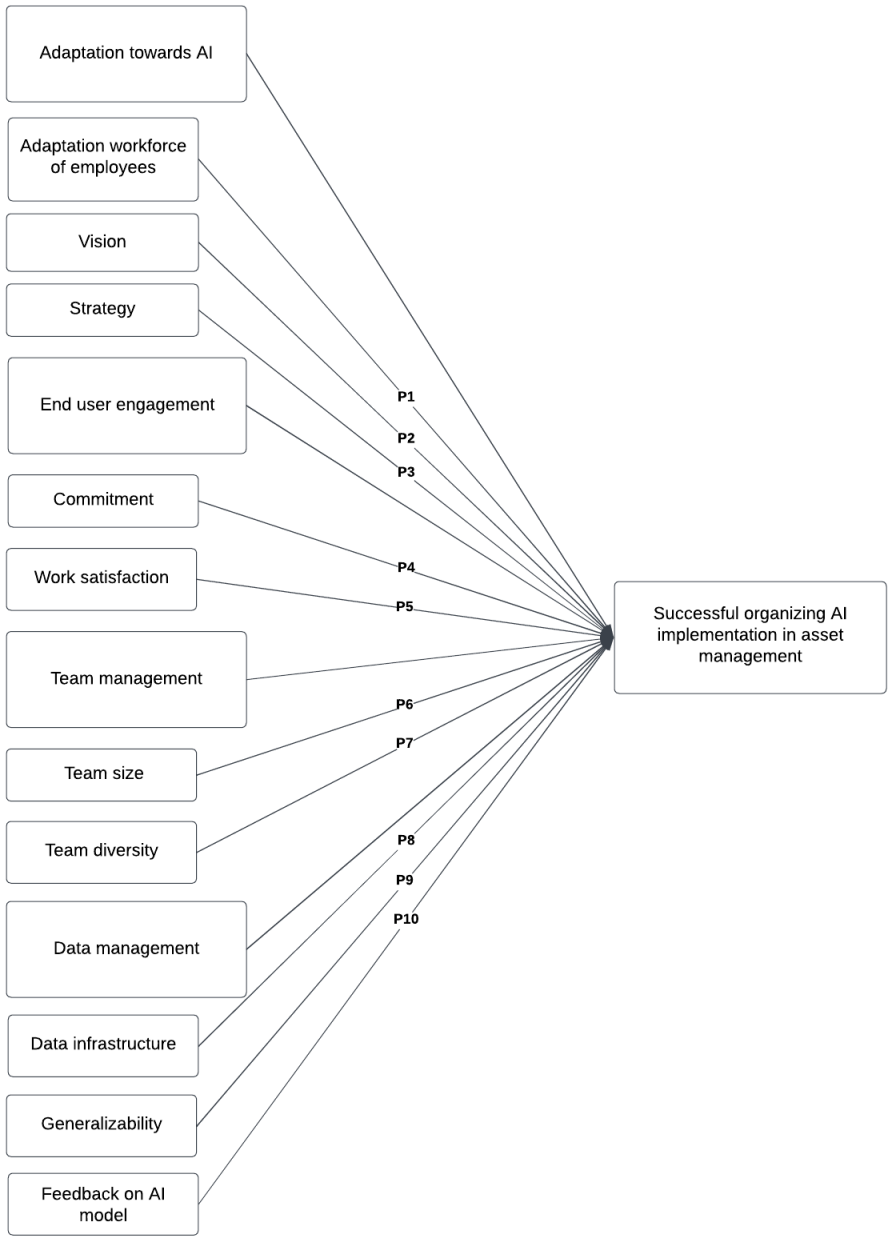

Figure 2 proposed conceptual model based on the identified propositions.

5 Discussion

5.1 Conclusion

This study offers valuable insights into how to successfully organize AI implementation in asset management. Serving as an inductive study, it establishes a foundation for future research, emphasizing the potential of AI implementation in asset management. This research attempts to extends AI implementation research to the domain of asset management. The diverse range of cases provided offers valuable insights into the given context.

First of all, the results suggest that in order to successfully organize AI implementation, adaptations are required across the organization. This includes adapting the workforce through the recruitment of AI knowledgeable employees, aligning the organizational vision to underscore data-driven work and innovation, and adopting a more flexible strategy to transcend the fragmentary nature of asset management. These adaptations promote cross-domain collaboration, efficient resource utilization, and innovation infusion throughout the implementation process. In addition, the end user engagement is key in successful AI implementation in asset management. Engaging end users by fostering commitment, urgency and managerial support amplifies their contributions, facilitating valuable feedback which is crucial for successful AI implementation in asset management. Emphasizing on work satisfaction of the end user during the implementation, as well as it in the business case further engages the end users, which further increases the engagement. Also, successful team management proves to be crucial in this context. A smaller team size is beneficial, as it ensures streamlined communication and adaptability. However, having a diverse team is also important, which needs to involve at least one domain expert who can support the subjective data in asset management, as well as IT professionals who possess AI knowledge. To attain high-quality data management and ensure successful AI implementation, organizations must establish a robust data infrastructure, involving the consistent capture of data over the long term. This transformation may require a shift from the traditionally short-term focus of asset management, highlighting the necessity for a more adaptable, long-term approach. Likewise, the generalizability of AI models is important, supporting cost-efficiency and facilitating cross-domain applications. Finally, maintaining high data quality hinges on end user engagement, further underscoring their role in refining the data quality required for AI, particularly given the subjective nature of asset management data.

So overall, in order to successfully organize AI implementation in asset management, it is essential to adapt your organization towards the new way of working, which involves new personnel and different data management infrastructure. The end user plays a crucial role in the implementation through facilitating feedback, in order to maximize feedback engaging them is important.

5.2 Theoretical implications

The first key contribution regards team management, with the key contribution of the role of a domain expert, in the implementation of AI in asset management. Team diversity generally contributes to successful AI implementation (Merhi, 2023). However, specifying how it relates to successful AI implementation is not mentioned. What is known that, if a project team consist of members from various areas, standardisation can be increased as well as innovation and learning (El-Adaileh & Foster, 2019). Also, having a more diverse team, increases perspectives and competencies in general software development, especially when problems are complex (Lee & Xia, 2010). This further highlights the careful consideration of interplay between technology and markets, for complex products when implementing innovation (Tidd & Bessant, 2020). In innovation, domain knowledge was shown to have a positive relationship towards innovative performance, in both incremental innovation as well as product with higher newness (Rundquist, 2012). This can be viewed as cross-functional teams and is also beneficial for innovation (Cooper & Kleinschmidt, 2007). Domain knowledge may also hinder AI implementation, like in low-resource areas where field workers resist it by falsifying or producing incomplete data (Sambasivan & Veeraraghavan, 2022). However, IT professionals failed to explain there, the need for user input or prioritize tasks that improve user satisfaction (Sambasivan & Veeraraghavan, 2022). This in return, highlights the need for end user engagement through work satisfaction, in order to receive the required domain input end user engagement will follow in the next contribution. So, collaborating with domain experts in team management is crucial for successful AI implementation in asset management. It allows for the integration of domain expertise and technical knowledge, ensuring that data is properly understood and utilized. This insight may not only be applicable for asset management but potentially also for other sectors.

The second contribution is towards strategic flexibility, for successful AI implementation and innovation in asset management. As operational asset management focuses on planning, asset data, and the execution of asset management plans (Gavrikova et al., 2020). Strategy in asset management is on short-term perspectives, with limited degree of freedom and its fragmentated strategy (Gavrikova et al., 2020). In asset management strategy often lacks cohesion, with separate processes for different assets like roads, trains, and bridges. When organizations initially introduce AI, they integrate it into their existing processes (Haefner et al., 2021). However, more flexibility, and cross-domain application would likely benefit successful AI implementation in this area. There is also a risk of not readjusting these processes, which could prevent AI projects from progressing beyond the pilot phase (Haefner et al., 2021). This hinders the realization of AI's full potential in asset management, as the integration of a strategic approach to asset management becomes increasingly important. It is crucial to strike a balance between innovative and routine utilization of AI to enhance strategic flexibility (Molina-Castillo et al., 2011). This aligns with the concept of AI ambidexterity, emphasizing the

importance of both exploration and exploitation activities to challenge the rapidly evolving technological environment, through strategic flexibility (Van de Wetering, 2022). Strategic flexibility plays an important role in guiding an organization to identify the most efficient means of executing its strategy, in utilizing its business and IT resources (Miroshnychenko et al., 2021). For asset management taking a more flexible approach to strategy may be beneficial to enhance innovation through AI for exploitation as well as exploration. However, this needs to be future researched.

The third contribution focuses on overcoming resistance through end user engagement. End user education and active involvement have been identified as important factors for AI implementation (El-Adaileh & Foster, 2019; Kim, 2019; Merhi, 2023). When implementing AI, addressing the concerns of end users is essential, as this could overcome resistance from the end user. A method for overcoming resistance is through introducing an AI tool as an assistant (Füller et al., 2022; Strohm et al., 2020). However, by addressing end users' primary concerns and demonstrating how the AI tool can alleviate tasks, a more positive attitude towards its adoption can be fostered. Work satisfaction was shown to be minimizing innovation resistance (Do Cho & Chang, 2008). Also, job satisfaction was shown to have a positive effect on AI adoption (Nguyen & Malik, 2022). However, given there is little to no literature to be found if work satisfaction, relates to end user engagement, influencing AI implementation. This findings in this thesis can be considered as fairly novel insights. So, for successful AI implementation focussing on tasks that enhance job satisfaction, may in return also impact AI implementation, since the end user is more involved and therefore more eager to provide necessary feedback.

The fourth contribution addresses the essence of early implementation of an AI model to gather feedback in asset management. Ensuring data accuracy and reliability is important for AI implementation, as low quality data can result in system failure (Merhi, 2023). Implementing an AI model early in the process is crucial for both data acquisition and feedback purposes (Fountaine et al., 2019). As well as to test innovation, to prove importance and boost acceleration in innovation, especially in the pre-incubation stage (Skvortsova & Nurulin, 2018). This could be done by having a prototype, to better acquire feedback from that end user (Füller et al., 2022). In asset management data is often complex and consist of various types of data like: textual, image, audio or video which all need to be integrated to generate value (Kumari et al., 2022). For asset management this may result in inadequate data, as was shown that the basis data collection was not always in order. Requiring organizations to gather new information, a situation commonly observed in asset management (Kumari et al., 2022). By having to deal with various types of data, which may be inadequate, the need for feedback for AI implementation is visible. While current research on AI implementation focus that the data needs to be of high quality, they do not focus on how to improve that data quality through feedback (Merhi, 2023). This paper highlights the possibilities that the data might be subjective, where there is no real high or low quality and it depends much more on the situation, which the AI system has to learn.

5.3 Practical implications

This study has practical implications on how to successfully organize AI implementation in asset management organizations. Currently, many asset management organizations lack the necessary knowledge to adopt AI due to its emergence as a field. To address this issue, this paper offers insights and guidelines on how asset management organizations can restructure themselves to embrace AI. While the focus on AI technology often is around its technical aspects, this paper acknowledges the of considering organizational and strategic factors (Fountaine, 2019). The study identifies the primary stakeholders responsible for adopting AI and highlights the importance of creating a supportive environment that enables ongoing data collection. The presence of reliable and high-quality data consistently over a period of time is essential for organizations. Given the limited use of AI in asset management, employees may not be familiar with the new work processes associated with AI, which hinders its full potential. Therefore, it is important to involve and motivate employees, preparing them for the transition to AI. One way to achieve this is by actively including them in the implementation process, allowing them to have a say in the selection and adoption of AI tools. This involvement facilitates valuable feedback from employees. Furthermore, providing a clear vision and strategy that emphasizes the importance of AI can enhance employee readiness and engagement.

5.4 Limitations

The first limitation regards the data collection method, it captures a static snapshot of the current development of AI implementation in asset management. Instead of researching an organization as a static snapshot, you could also see the implementation as a dynamic process, where some factors might be more important at certain moments (Tsoukas & Chia, 2002). It was not feasible to experience the entire process of AI implementation, within the limited timeframe of a master thesis programme. To minimize this limitation, respondents were asked to recall critical incidents that highlight significant past events (Gremler, 2004).

Secondly, this research was conducted as part of a master's thesis, which required individual completion within a limited timeframe. In contrast to the usual practice of multiple researchers performing the coding process and comparing results (e.g., independent parallel coding), the coding process in this case was conducted independently (Thomas, 2006). Through comparing results among researchers, interpretations of informants often a arise. This engages discussion, and may lead to revisiting codes to reconcile to the different interpretations and leads to a higher trustworthiness of the data analysis (Gioia et al., 2013; Lincoln & Guba, 1985). However, to mitigate potential biases, my mentor, a professional researcher, oversaw, discussed, and verified both the coding process and the results, which can be viewed as a form of member checks (Thomas, 2006).

Lastly, the target group of this research were organizations, relating to asset management, in the infrastructure industry in the Netherlands, who have experience with AI. It became evident during the

recruitment process of respondents that most organizations in this target group are not yet ready to implement AI, limiting the availability of respondents and practical experience in this area. The informants who did have experience were leading the field in the infrastructure industry, regarding AI. Through focusing on this target group, this limits the diversity of this research. Also, in the Netherlands, infrastructure projects often involve the government, which holds ownership over a significant portion of the infrastructure, including roads, train tracks, bridges, and tunnels.

5.5 Future research

The first theme that requires future research is to validate the significance of the dimensions identified in this study. These dimensions were derived from interviews using an inductive approach, lacking direct theoretical operationalization. Therefore, it is essential to conduct quantitative studies to determine their applicability in the context of asset management. Additionally, top management support was not considered a second-order concept and was not frequently mentioned by the informants. However, in other AI implementation research, top management support has been identified as one of the most common factors (El-Adaileh & Foster, 2019; Merhi, 2023). Hence, it is necessary for future research to investigate whether management support is indeed not a valuable factor for AI implementation in asset management.

The second theme, some 2nd order concepts where not shown in regular AI implementation theory like: team size, autonomy, and end user engagement for domain knowledge cannot be directly associated as success factors for AI implementation theory in general (El-Adaileh & Foster, 2019; Merhi, 2023). Therefore, these concepts require future research as to validate whether they are also applicable to AI implementation theory in general.

The third theme involves the strategic flexibility and combining of strategies over assets could potentially facilitate further development of AI and makes it easier to implement. This may lead to generalizability of AI systems and easier budgeting of new projects. While this may not be a pressing issue during the initial stages of AI adoption, further progress beyond pilot projects requires changes in existing processes (Haefner et al., 2021). Strategic flexibility could promote innovation in asset management, as its utilized business and IT resources (Miroshnychenko et al., 2021; Van de Wetering, 2022). However, considering the static nature of assets and the technical systems associated with them, it remains to be researched and verified whether combining assets through strategy is actually feasible.

The fourth theme, focuses on exploring the connection between strategic asset management and AI. Gavrikova et al. (2020) identified strategic asset management as a distinct research category, and this study highlights the potential link between AI and asset management. Further investigation is needed to understand how AI can contribute to future strategy in asset management. Strategic asset management is seen as means for long-term survival in turbulent environments (Gavrikova et al.,

2020). From this research can be concluded that current asset management practices tend to have a more short-term focus. Examining how AI can bridge this gap and enable long-term strategic planning within asset management would be a valuable area for future research.

Finally, this study primarily examined asset management within the infrastructure sector, where the government plays a crucial role as a significant stakeholder, owning a majority of assets in the Netherlands (Rijkswaterstaat, 2023). Although the government's involvement was not directly considered in this research, it presents an intriguing stakeholder to explore further. Special challenges for AI implementation for government are: transparency, accountability, security issues, data privacy and unfair decision making (Salam et al., 2023). Specifically, it would be worthwhile to investigate the role of the government in the implementation of AI in asset management. Given their accountability for the assets, the government may have distinct priorities and considerations compared to typical organizations. Understanding the unique perspective and contributions of the government in leveraging AI within asset management is an important area for future investigation.

6 Appendix

6.1 Preparation questions

1. What organization do you work for and what is your role there?
2. What are your experiences with AI?
3. What are your experiences with asset management?

For the interview, we will discuss two cases where AI has been implemented. I would like to talk about two separate cases, one being successful and the other being sincerely less successful. However, if you only have experience with one scenario of AI in asset management, then we can discuss both the positive and less positive aspects of that case.

The following questions are for the successful case1:

1. Can you explain how the AI system works in general?
2. Can you briefly describe the process of AI implementation?
3. How did the organization measure the success of the AI implementation?
4. What was the original problem that AI needed to solve?
5. What were some unique aspects of this case?

The following questions pertain to case 2, where challenges were encountered:

1. Can you explain how the AI system works in general?
2. Can you briefly describe the process of AI implementation?
3. How did the organization measure the success of the AI implementation?
4. What was the original problem that AI needed to solve?
5. What were some unique aspects of this case?

6.2 Interview questions

Introduction questions

- Small introduction, it takes approximately an hour
- Research ethics, everything will be made anonymously
- Permission audio recording
- No good or wrong answers

Case specific questions

The following questions are asked two times, one time per case.

1. Potential clarification questions on the survey responses?
    a. How does the AI system work?
    b. Why was this AI system chosen?
2. Clearly defining the problem that AI needs to solve:
    a. • How did the problem arise?
    b. • When did the problem arise?
    c. • Where did it occur? Which departments?
    d. • Why is it a problem?
    e. • What would happen if AI was not used for this application?
3. What was a special aspect of this case? (Referring to the survey if necessary)
    a. • What was the impact?
    b. • Why was it special?
    c. • How did it come about
4. Which factors contributed to the successful implementation of AI in this case?
    a. • Why did these factors help so much?
    b. • Were they expected beforehand?
    c. • Who was responsible for these factors?
    d. •Did this factor contribute to a change?
    e. In other words, did this factor lead to its application in other process optimizations?
5. Which factors hindered the success of implementing AI in this case?
    a. • Why was this a problem?
    b. • Was it expected beforehand?
    c. • Could it have been prevented?
    d. • Who was responsible for this?
    e. • How was this problem eventually overcome?
    f. • Have any changes been made to the working method due to this problem?
    g. In other words, how do you ensure that this problem will not happen again?

6. What were the consequences of the AI tool on asset management?
    a. • Were there any unforeseen expectations?
    b. • What were the consequences of the AI tool on the organization?
    c. • Were there any unforeseen expectations?
7. Looking back on this case, what lessons have you learned from this AI project?
    a. • Why?
    b. • Are there any practices that you now do differently on a regular basis?

If the respondent has not told anything about the following questions himself, these questions can be asked. Since it is inductive research, the main focus is to let the respondent introduce these questions, instead of the interviewee.

1. What do you expect the impact of AI will be in the future, in asset management?
    a. What opportunities and challenges do you anticipate?
2. How has the organization ensured that the AI solution is ethically responsible?
    a. Have specific safeguards or controls been put in place?
3. How does the company handle responsibility in relation to AI?
    a. Who makes the decisions, who implements, who evaluates?
    b. Does this vary?
4. What is the role of management in the successful implementation of AI?

6.3 Revised interview questions

After interview 5, two questions were added to better fit the research question, since the first interviews were too much focused towards the technical aspect of AI in asset management.

Questions added:

What where the consequences of AI for the organization?

Were there also negative consequences for the organization through AI?

6.4 Quote table

Quote number	Chapter	Quote
1 **Case 9**	Adaptation workforce of employees	**R6:** ´´Normally you would say, my job is being taken away or something. But the point is that, from what I see at least, it's actually advantageous. Because we already have capacity shortages, so there are already too few people. ´´
2 **Case 8**	Shift employees	**R5**: ''Data and information management is a specialized field. It's not something you casually do on the side. Often, you encounter conversations with project leaders, project managers, contract managers, and asset managers who mistakenly believe they possess some kind of magical wand. They think, ''I have a box of data, I'll wave the wand, and it will work." The reality is a bit different. While we excel at designing, building, and maintaining technical aspects, we still have a lot to learn collectively when it comes to handling information and extracting value from it.''
3 **Case 1 & 2**	Commitment	**R1:** ''so in case 1, the urgency was very high. The user was told that this had to be done, no matter what, this year. So, you can tell that there is quite a lot of pressure and then, you quickly know where the areas for improvement are. In the other case, processing the output took a longer time, and if the urgency is not that high, you can see that the usage is limited, because the model does not receive sufficient feedback to make it work successfully.''
4 **Case 8**	Work Satisfaction	**R5** ''Ultimately, efficiency is an aspect that we should not overlook. It contributes to the overall work satisfaction of employees. There is a lot of frustration towards the inability to find information at the right moment. This is a widely recognized problem in the installation world and construction.''
5 **Case 14**	Work satisfaction	**R10** ''Ultimately, the technology serves the purpose of the product. We prioritize user-friendliness because it makes the product attractive to work with. For example, having a responsive and visually good-looking website that is easy to use.

		These aspects are just as important to people as the underlying technology itself.''
6 **case 11**	Team size	**R8:** ''You should have a maximum group size of six people. That is my team size, and you can still make use of other specialists. But that group of 6 people determines the direction and can switch very quickly. The big advantage of this is that you have a very short line of communication.''
7 **Case 9**	Team diversity / adaptation workforce of employees	**R6:** ''From the project team, you would need a maintenance engineer, executor, inspector, and asset manager. […] At least one of these individuals should be included in the team to initiate the setup of a pilot project or to start with a specific asset group. […] This integration is considered one of the key success factors in implementing AI in asset management.''
8 **Case 14**	Team diversity / feedback on AI model	R10: ''An inspection is always somewhat subjective. So, it's difficult to categorize it, because one person may consider it serious, while the other may consider it very serious. So yes, there are guidelines, but there is always some subjectivity involved. And it's challenging to eliminate that completely.''
9 **Case 14**	Data infrastructure	**R10:** ''Instead of focusing solely on the end result, the emphasis should be on centralizing data collection. This is something that still happens a lot in asset management, especially among engineers. There are companies that simply aim to deliver a report for Company X, and once that report is delivered, they consider their work done. However, it is much more valuable to think in the long term and consider that multiple reports and the data used in those reports can be useful for training models and automating processes in the future. Therefore, it is important to adopt a structured, long-term mindset and think proactively.''
10 **Case 13**	Data infrastructure	**R9:** ''You need to consider all seasons throughout the year before you can determine something meets the requirements.
11 **Case 2**	Data infrastructure	**R1**: ''you need to ensure that the model takes into account various situations and is trained on information from all regions. Multiple seasons, day, and night. Yes, you should be able to

		handle all those different situations and not just train a model on a beautiful summer day in Rotterdam, so to speak.''
12 **Case 12**	Generalizability	**R9:** ''The most important lesson I have learned is not specific to this, but make sure that you know in advance that whatever you build, you can continuously reuse it. [...] if you can't just plug in and go live, then I would choose a different use case.''
13 **Case 9**	Generalizability	**R6:** "We also need to create a business case because, well, it already costs money to develop all of that. Now, it is important, of course, to look at where that business case actually lies, right? And can you spread it across multiple projects as well."

6.5 Case description

Respondent 1 - Case 1

The issue arose from a lack of clarity in their digital systems regarding the exact location and specific information of parts within their assets. Because other companies perform the maintenance of the assets, they replace parts sometimes without the organization's knowledge. To gain a more comprehensive understanding of their assets, they devised a solution in the form of a device capable of capturing videos and identifying the various components of the assets. The primary objective was to gain the types of parts of the assets, the location, and integrate this information into SAP for better management and tracking.

Respondent 1 - Case 2

Similar to case 1, but for a different component of the asset. This case was less successful because the technology was used for a different type of component, resulting in a longer processing time, which caused it to not pay off entirely. Although the technology works fine, the extended processing time and other priorities of the end user have prevented it from living up to its promises so far.

Respondent 2 - Case 3

In the Netherlands, several companies are responsible for managing the infrastructure assets of various regions. The asset management companies need to conduct a baseline assessment to determine the status of the infrastructure. This is done by the start of a tender like a baseline assessment and then later done each year to determine the maintenance plan. These contracts typically span longer periods, usually lasting between eight to ten years. The scope of these contracts includes managing roads, streetlights, crash barriers, and other elements associated with the roads. To carry out the baseline

assessment, a specialized vehicle equipped with a special camera that uses lasers. This camera captures videos and creates a digital twin of the assets. The digital twin is then processed by an AI model, which is trained to identify and learn about any abnormalities or issues with the assets. For instance, if a street sign is bent, the AI model detects and registers this information. All identified anomalies are further reviewed by experts who assess whether they require fixing or not. This feedback is then incorporated into the AI model, enhancing its capabilities and accuracy. Ultimately, this process ensures efficient asset management and timely maintenance based on real-time data and AI-driven insights.

Respondent 2 - Case 4

The second case involved the same technology, but it faced more challenges in acquiring the new digital twin. For instance, parking cars caused inaccuracies in the data, leading to the need for manual intervention to rectify the issues which caused a delay. As a consequence, the client expressed dissatisfaction, because they did not understand why it took so long.

Respondent 3 – Case 5

This case involves software that can predict malfunction of an asset based on changes in its energy use. The technology itself is generic and is sold to several organizations. For the implementation is further zoomed in towards specific examples of different clients of things that went explicitly good or bad.

Respondent 4 - Case 6

The interview was with employees who are responsible for data driven asset management for the government. The case was around predicting when an asset needed cooling, based on a few factors like: temperature and sensors. The goal was to predict if the asset needed cooling over a longer period. This model is by itself not an AI model, more a regression model that matches the temperature with the reaction of the asset. During this interview the focus was more towards resistance or what the organization needs to use AI.

Respondent 5 -Case 7

In asset management, at the beginning of a project, numerous drawings and documents are available to support mechanics and provide essential information. However, a challenge arises because these drawings and support documents come from different organizations or departments, each utilizing their own IT systems. Consequently, there is a loss of data integration. To address this issue, an AI model is employed to summarize the data and consolidate specific documents. This approach ensures that mechanics receive the necessary information they need without being hindered by the data fragmentation caused by disparate IT systems.

Respondent 5 - Case 8

The second less successful case involved predicting the lifecycle of an asset for a tunnel. The objective was to create a model capable of anticipating when the asset might malfunction. There was insufficient data available to develop a highly accurate predictive model. The initial predictions generated from the limited data were too generalized to be effectively utilized. Despite this setback, the company decided to retain the model, and there is a possibility of further implementation if sufficient data becomes available in the future.

Respondent 6 - Case 9

Similar to the scenario described by respondent 2, this case also took place at the same company but involved a different project.

Respondent 7 - Case 10

This project revolved around designing an asset. The process involved providing certain parameters to a model, which then generated a design for the asset. This design was then evaluated by an individual to check its feasibility. The model continuously learned from the feedback received, allowing it to improve and refine its design over time.

Respondent 8 - Case 11

In this case, the company worked on developing its own version of ChatGPT using internal data. Initially, the software is being used for writing reports within the company, but there are plans to explore the possibility of selling it to external customers as well.

Respondent 9 - Case 12

In this case, a model was developed to aid in water purification by identifying toxic emissions and responding appropriately. The model uses data to predict the behavior of the purification system. Additionally, a second model is built using reinforcement learning to improve control strategies. This new model takes into account water quality as well as factors like emissions and energy consumption. The ultimate goal is to optimize the purification process, reducing emissions and energy usage while ensuring the maintenance of high-water quality.

Respondent 9 - Case 13

In the second case, the objective was to use drones and an AI model to count the number of animals passing through a specific field during a particular time of the year. However, the project encountered challenges because it was a one-time action, requiring significant effort for a singular outcome. Despite the technology's effectiveness, the overall effort invested in the project outweighed the results achieved.

Respondent 10 – Case 14

This case involves a consultancy firm that has created a road inspection service using video capture and AI technology. The program utilizes an AI model to identify damages on the road's surface. This software is used by various organizations, both within and outside the Netherlands, for road inspection purposes.

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