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A Sociotechnical Perspective on Digital Twins and Edge AI

A Case Study of the NexTArc Project Through the Technology-Organisation-Environment Framework

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Abstract

Digital twins and Edge AI are increasingly discussed as technologies that can support data-driven decision-making in complex environments. However, the implementation is not only a technical issue for the development but also depending on organisational and environmental factors. This thesis examines how digital twins and Edge AI are developed and implemented in a complex sociotechnical setting through an in-depth case study of the EU-funded NexTArc project, with a specific focus on Use Case 1 and the development of a digital city twin for the Marieberg district in Stockholm. The purpose of the study is to identify technological and organisational success factors, as well as challenges connected to the implementation and integration of digital twins and Edge AI. The analysis is based on the Technology-Organisation-Environment (TOE) framework. It is conducted through a qualitative case study, using semi-structured interviews with ten participants involved in the project. The empirical material was analysed through a thematic analysis.

The analysis resulted in six themes, consisting of the digital twin as a sociotechnical system, data as the core enabling resource, Edge AI as an enabler of local data processing, integration as the main implementation challenge, collaboration between partners, and NexTArc as a platform for learning and capability-building. Furthermore, the findings show that successful implementation depends on alignment between technological, organisational, and environmental factors. Technological components such as sensors, data pipelines, APIs, metadata, edge devices, and user interfaces are necessary, but they only create value when they are coordinated across organisational boundaries. The study further shows that key enabling factors include access to relevant data, clear data structures, metadata, standardised interfaces, shared definitions, role clarity, physical meetings, and knowledge exchange. The main challenges contain missing or inaccessible data, unclear definitions of digital twins, technical integration, unclear partner contributions, and coordination complexity in a large multi-partner project. The thesis contributes by conceptualising implementation as an alignment process rather than a linear technical process, and by providing practical implications for future digital twin and Edge AI initiatives.

The implications for future research include following NexTArc as the project advances from a proof-of-context phase towards more integrated and operational solutions. It also includes the possibility to investigate how additional stakeholders such as urban planners, policymakers, citizens, and future users understand and use digital twins. Further, it would be interesting to compare NexTArc with similar projects to examine which findings are specific to this project and which are relevant to other digital twins and Edge AI initiatives.

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Digital teknik används i allt större utsträckning för att förstå, planera och förbättra komplexa miljöer, exempelvis städer, energisystem och industriella processer. I takt med utvecklingen av sensorer, kameror, byggnader och uppkopplade system produceras data i en ökande hastighet, vilket ökar behovet av lösningar som kan hantera den producerade information effektivt, säkert och i nära anslutning till datakällan. Två centrala tekniker i denna utveckling är digitala tvillingar och Edge AI. En digital tvilling kan beskrivas som en digital representation av en fysisk miljö eller ett system, som kan användas för att samla data, visualisera information, analysera och testa möjliga scenarier. Edge AI innebär att artificiell intelligens tillämpas nära datakällan, istället för att skicka rådatan till den centrala tjänsten.

Denna uppsats undersöker hur digitala tvillingar och Edge AI utvecklas och implementeras i en komplex socioteknisk miljö. Denna studie genomförs genom en fallstudie på det EU-finansierade projektet NexTArc, med särskilt fokus på Use Case 1, som utvecklar en digital tvilling för området Marieberg i Stockholm. Syftet med studien är att identifiera teknologiska och organisatoriska framgångsfaktorer samt utmaningar vid utveckling och implementering av digitala tvillingar och Edge AI. För att genomföra denna analys används Technology-Organisation-Environment-ramverket (TOE). TOE-ramverket visar att teknologisk utveckling inte enbart påverkas av de tekniska aspekterna, utan även av organisationen och den omgivande miljön.

Studien genomfördes som en kvalitativ fallstudie. Det empiriska materialet består av semistrukturerade intervjuer med tio deltagare som på olika sätt är involverade i NexTArc och Use Case 1. Intervjuerna analyserades genom en tematisk analys, vilket innebär att återkommande teman identifierades i materialet. Analysen var även abduktiv, vilket innebär att resultaten utvecklades utifrån både det empiriska materialet samt TOE-ramverket.

Analysen resulterade i sex centrala teman. Det första temat visar att den digitala tvillingen bör förstås som ett sociotekniskt system, inte enbart som en teknisk visualisering. Den digitala tvillingen består av data, teknisk infrastruktur, modeller, användargränssnitt, människor, organisationer och beslutsprocesser. Det andra temat visar att data är den viktigaste möjliggörande resursen för både digitala tvillingar och Edge AI. Utan relevant och tillgänglig data är det svårt att skapa en digital tvilling som kan användas för analys, simulering och beslutsstöd. Det tredje temat påvisar att Edge AI möjliggör lokal databehandling, vilket minskar mängden data som behöver skickas vidare. Det har även möjlighet att stärka integritet och säkerhet, minska fördröjningar, samt avlasta centrala system. Det fjärde temat visar att integration är den största utmaningen gällande implementering. Det räcker inte att enskilda tekniska komponenter fungerar var för sig, de behöver kopplas samman till ett fungerande helhetssystem. Det femte temat beskriver samarbetet mellan partnerorganisationerna. Eftersom NexTArc består av flera organisationer krävs tydliga roller, gemensamma definitioner och kontinuerlig kunskapsdelning. Det sista och sjätte temat visar att NexTArc även fungerar som en plattform för lärande och kapacitetsbyggande, där organisationer kan testa lösningar, utveckla ny kunskap och bygga relationer för framtida projekt.

Studiens slutsats visar att utvecklingen och implementeringen av digitala tvillingar och Edge AI inom detta projekt inte bör betraktas som en linjär teknisk process. Den bör istället ses som en samordnings process där teknologiska, organisatoriska och miljörelaterade faktorer bör anpassas till varandra. De tekniska komponenterna är nödvändiga, men de skapar inte värde utan tydliga roller, gemensamma begrepp, tillgång till data, fungerande samarbete och en gemensam förståelse för vad den digitala tvillingen ska bidra med.

Resultatet från denna studie leder till flera praktiska rekommendationer för NexTArc samt liknande projekt. Projektet bör tydliggöra definitionen av en digital tvilling, prioritera data och metadata som centrala delar av infrastrukturen, behandla integration som en huvudfråga redan i början och fortsätta använda fysiska möten och workshops för att stärka samarbete och kunskapsutbyte. Studien genererade även implikationer för framtida forskning. En av dessa är att genomföra en liknande studie av NexTArc i en senare fas av projektet, för att undersöka hur utvecklingen av projektet genomförs. Vidare hade det varit intressant att undersöka perspektiv från användare, medborgare, planerare och beslutsfattare utifrån hur de förstår och använder digitala tvillingar och Edge AI. Avslutningsvis hade det varit intressant att jämföra NexTArc med liknande projekt för att undersöka vilka resultat som är direkt kopplade till NexTArc och vilka som är relevanta för andra liknande projekt.

Preface

This research was conducted on behalf of Cicor, Uppsala, as a part of the Master's Programme in Sociotechnical Systems Engineering at Uppsala University. I would like to take this opportunity to thank everyone who has supported and assisted me throughout this process. First of all, I would like to thank Cicor for giving me the opportunity to conduct my thesis within the organisation. I would like to give special thanks to my supervisors at Cicor, Adam Laurell and Elias Kettunen, for their valuable insights and feedback throughout the process. Furthermore, I would like to thank all interview participants for their time and insights, providing invaluable contributions to my research. Finally, I would like to express a special thanks to my subject reviewer, Anna Eckerdal, for supporting me, for the insightful feedback, and for being available throughout the whole process.

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1. Introduction

Modern society is becoming increasingly dependent on digital technologies to understand, manage, and improve complex systems. This development creates new opportunities for more informed decision-making, automation, and optimisation, but it also creates challenges regarding data processing, privacy, and system complexity. Artificial intelligence (AI) has become an important part of this development, with recent advances in machine learning (ML), which has broaden to possibilities of AI, including the ability to process large amounts of data and identify patterns that can support decision-making in complex environments (Ergen, 2019; Russell & Norvig, 2021; Sheikh et al., 2023). At the same time, the increasing use of connected devices, sensors, and data-generating systems has created a need for solutions that can process information efficiently, safely, and closer to where the data is produced. This is particularly relevant in urban settings, where data from buildings, energy infrastructure, sensors, and users must be connected in order to support more sustainable and informed decision-making.

Throughout this development, digital twins have become more important. A digital twin can be understood as a combination of the digital representation of the physical product, the virtual product, and the connection of data and information (Grieves, 2014). In a smart city context, digital twins can combine real-time data, simulation, visualisation, and analytics to support monitoring, scenario testing, and decision-making (Ivanov et al., 2020; White et al., 2021). However, there are differences in the definitions of digital twins and in how they are used (Kreuzer, 2024; Kritzinger, 2018), which indicates that the practical implementations of digital twins remain challenging.

Edge AI combines artificial intelligence with edge computing by enabling ML models to be trained and executed close to the data source, instead of relying on centralized cloud infrastructure. Edge AI has the possibility to reduce latency and bandwidth usage, increase resilience, and improve privacy. This is due to the reduced amount of data that needs to be transferred (Meuser et al., 2024). Edge AI can also contribute to energy efficiency and cost optimisation by reducing data transmissions (Gupta, 2025). By using Edge AI together with digital twins, it can support local processing of sensor data, image data, and other data streams before the information is sent to the central digital twin. This makes Edge AI particularly relevant for urban environments, where large amounts of data are produced and where the data can be sensitive and time-critical.

The empirical setting for this study is the EU-funded NexTArc project, which aims to accelerate the adoption of trustworthy, low-power, and secure Edge AI across urban and industrial environments (European Commission, 2025). The NexTArc project includes several use cases, but this thesis focuses on Use Case 1, which focuses on the development of a digital city twin for Marieberg in Stockholm to create a smart, sustainable, and livable urban district (NexTArc, 2025). The digital twin and Edge AI are not only technical solutions, but also parts of a broader sociotechnical system involving data infrastructure, sensors, user interfaces, and collaboration between partners.

To analyse the complexity of the case, the thesis uses the Technology-Organisation-Environment (TOE) framework. It explains technological innovation as shaped by the technological context, the organisational context, and the environmental context (Baker, 2011; Tornatzky & Fleischer, 1990). The framework is suitable for analysing NexTArc, where the development and implementation of digital twins and Edge AI depend on both technical components, organisational collaboration, and environmental aspects. By analysing NexTArc as an in-depth case study, this thesis aims to contribute with empirical findings regarding how digital twins and Edge AI are developed and implemented in practice, and to identify success factors and challenges that can support future development of digital twins and Edge AI.

1.1 Purpose

The purpose of the study is to examine how digital twins and Edge AI are developed and implemented in a complex sociotechnical setting, through an in-depth case study of the EU-funded NexTArc project, with focus on Use Case 1. The study aims to identify technological and organisational success factors, as well as challenges associated with the development and implementation of digital twins and Edge AI. The analysis is grounded in the Technology-Organisation-Environment (TOE) framework, which is used to structure and interpret the technological, organisational, and environmental factors.

Based on the empirical insights, the thesis further aims to develop practical recommendations that can support the partnering organisations in ongoing and future digital twin and Edge AI initiatives.

1.2 Research Questions

1. How do the technological and organisational factors affect the development and implementation of digital twins and Edge AI within the NexTArc Use Case 1?
2. Which technological, organisational, and environmental factors enable successful implementation and integration of digital twins and Edge AI across organisational boundaries in the context of the NexTArc project?

1.3 Delimitations

This study is delimited to a single case study within the EU-funded NexTArc project. The study focuses exclusively on Use Case 1, which concerns the development of a digital city twin for the Marieberg district in Stockholm. Other use cases, related to industry and mobility, are not included in the empirical analysis. This delimitation enables a more structured in-depth analysis.

The study is further delimited by its empirical material. The findings are based on semi-structured interviews with participants involved in the development, coordination, and implementation of the NexTArc project. The study therefore reflects the perspectives of project leaders and developers. It does not include end users, citizens, policymakers, or other actors who may use or be affected by the project.

Furthermore, the study captures the NexTArc project during an early development phase. This leads to the analysis concerning the development and implementation phase from that perspective. The study is therefore context-dependent for early-stage development and implementation. The study does not aim for statistical generalisation, but rather from analytical and context-dependent understanding that may be relevant for other similar projects.

2. Background

This section presents a technical background needed for the NexTArc case study. It introduces artificial intelligence, Edge AI, digital twins, and the NexTArc case.

2.1 Artificial Intelligence, Machine Learning, and Data-Driven Decision-making

Artificial intelligence (AI) has existed for decades, far longer than the rise of generative AI that is widely known today. The term artificial intelligence was introduced at the 'Dartmouth Conference' of 1956, organised by John McCarthy (Ergen, 2019; Sharma, 2024), marking the establishment of AI as a formal research field (Russell & Norvig, 2021) There is a lack of a universal agreed-upon definition, which Sheikh et al. (2023) describes can be explained because the field is complex and constantly changing. The lack of definition of AI derives from the lack of definition of human intelligence. As the research of human intelligence advances, it enables the development of AI and moves closer to a more unified definition. One definition by Sharma (2024) explains AI generally as the process of creating intelligence using non-biological materials and procedures. Another broad definition of AI is explained as systems that interpret their environment and act to achieve optimal outcomes, operating autonomously, persisting over time, adapting to change, and pursuing specific goals (Russell & Norvig, 2021). This definition is the most relevant for this study and will therefore be used as the basis for understanding AI in this thesis. AI has the possibility to enable digital systems to analyse data, identify patterns, and support prediction, optimisation, and decision-making. This is particularly relevant in complex systems where large amounts of data are generated and need to be transformed into useful information. AI is therefore seen as the technical human judgement for data-driven analysis (Russell & Norvig, 2021; Shrestha et al., 2019).

As of today, the majority of AI advancements and applications are categorised as ML. ML is relevant for this study as it focuses on how models can learn from data and apply these patterns to new situations. ML models are trained on data to identify statistical relationships that can be used for prediction, classification, optimisation, and decision-support (Ergen, 2019). ML is a subset of AI which has the possibility to make predictions from inputs and outputs (Mueller et al., 2025). ML algorithms are statistical instruments that find patterns in a big amount of data. These patterns are relationships between input and output, and can therefore be used to make predictions of new input data (Ergen, 2019). ML models are mathematical and statistical models that can associate certain inputs with outputs, with no understanding of the actual meaning of the algorithm. This is made through training that provides an algorithm using large amounts of data of inputs and outputs (Mueller et al., 2025). This makes ML important for systems with large amounts of data, where optimisation and decision-support are crucial.

In this thesis, AI and ML are relevant because they create the useful analytical capabilities needed to transform data into useful outputs, such as prediction, classification, optimisation, and decision-support. These are important for systems that generate large amounts of data, where the data need to be understood and used. This makes AI and ML important technical foundations for understanding the development and implementation of Edge AI and digital twins (Kreuzer et al., 2024).

2.2 Edge Computing and Edge AI

As data is increasingly produced at the edge of the network, it would be more efficient to process the data at the edge, closer to where it is produced. Edge computing refers to enabling technologies to compute at the edge of the network. This means that the computing takes place close to the sensors, devices, or local network nodes, which leads to the possibility to transfer less data to the central cloud infrastructure (Shi et al., 2016). Internet of Things (IoT) devices and sensors collect information from the physical environment. The data and information needed may come from sensors, cameras, and other connected infrastructure (Minerva et al., 2020). Edge computing has therefore become relevant in environments connected to IoT, where connected devices generate large amounts of data that require low-latency processing and privacy-policy enforcement (Satyanarayanan, 2017).

Edge AI integrates artificial intelligence and edge computing by having the inference of ML models to be trained or executed closer to the data source, instead of in the centralised cloud infrastructure (Meuser et al., 2024). This makes it possible to process and analyse locally generated data at the edge of the network, enabling faster decisions and allowing only useful information to be sent to the central cloud infrastructure (Singh & Gill, 2023).

Edge AI is often implemented on edge devices or embedded systems. Edge devices include sensors, cameras, embedded servers, and other local computing units (Singh & Gill, 2023).

Embedded systems are computing systems integrated into larger physical or technical systems (Marwedel, 2021). These devices have limited processing power, memory, storage capacity, and energy availability. This makes Edge AI challenging, as the models must adapt to operate efficiently (Singh & Gill, 2023).

The features of Edge AI makes it relevant in environments where large amounts of data are produced. This method reduces latency, lowers bandwidth usage, enhances data privacy, and enables faster and more resilient decision-making. This is because Edge AI can reduce the need to transfer raw data, when the data are processed locally (Meuser et al., 2024). Furthermore, it enables stronger privacy policies as the data are processed prior to transferring the data further (Satyanarayanan, 2017). This is especially relevant for domains such as smart cities, healthcare, autonomous driving, and industrial automation. Furthermore, Edge AI can support more resilient systems as devices can process data and make decisions locally, without depending on the connection to the cloud (Meuser et al., 2024).

Despite the advantages of Edge AI, there are limitations and implementation challenges worth mentioning. Since Edge devices have limited computational capacity and energy resources, AI models need to be optimised to be able to run locally. This leads to the necessary development of energy-aware algorithms and hardware optimisation. These techniques may lead to a compromise between accuracy, speed, and energy use. Edge AI systems must address these challenges when they are integrated into complex real-world environments (Meuser et al., 2024).

Edge AI has a significant potential, but faces two major challenges, trustworthiness and sustainability. The key elements of trustworthy Edge AI include transparency, fairness, and robustness. Transparency implies the ability to see what is happening in a system. The fairness of the system includes that the system should be free from unfair bias, discrimination, and stigmatisation. For Edge AI, fairness is a concern when the bias solely comes from the algorithm. The robustness attribute refers to the system's ability to remain functioning under disturbance. For Edge AI, it is important that the system can handle failures and incorrect feedback without failing. Sustainable Edge AI refers to development and deployment of the systems that minimise energy consumption, reduce resource waste, and support long-term ecological and societal sustainability. It involves power saving, circular economy, and sociotechnical co-design (Ding et al., 2021). Edge AI also faces implementation challenges, including resource limitation, security and privacy, sustainability, interoperability, and system resilience. The challenges arise as Edge AI often operates on systems with limited computing capacity, while still needing to process sensitive data, interact with complex systems, and function in real-world environments (Meuser et al., 2024).

2.3 Digital Twins and Digital City Twins

Digital twin technology is an emerging technology associated with Industry 4.0 (Nochta et al., 2021). Industry 4.0 describes how humans interact with machines and IoT technology, including AI and ML, characterised by the shift in decision-making from humans to machines (Syam & Sharma, 2018). The concept of digital twins was first introduced in 2003 by Grieves (2014). Since then, the definition of the digital twin is difficult to define in a unified way, as the concept is used differently whether it is described in research and industry context. Fuller et al. (2020) explain that a lot of definitions fail to clearly distinguish digital twins from general digital models of simulations. A central feature for digital twins is the interaction between a physical object or system and its digital representation through data flows. This means that the digital twin is a connected system that can support monitoring, simulation, and decision-making (Fuller et al., 2020). Digital twins consist of three parts, the physical product, the virtual product, and the connections of data and information (Grieves, 2014).

When discussing digital twins, it is important to make a distinction between a digital model, a digital shadow, and a digital twin. A digital model is a digital reflection of a physical object, which does not use any automated data exchange between the physical and the digital objects. A digital shadow goes further than a digital model, with an automated one-way data flow between the physical object and digital object. The digital twin goes even further, with fully integrated data flow in both directions between the physical object and the digital object (Kritzinger et al., 2018). The differences between these definitions are important as it shows that the digital twin requires more than a static model.

A digital twin of a city or a part of a city is built up by a system of digital twins, which supports synchronisation with the state of the city through data generated from sources in real time. Examples of such systems include information about traffic flow, outdoor surveillance cameras, temperature, humidity, etc. The collected data can support the operation of the digital twins of the city. These digital twins have different types of features, including monitoring the current state of the environment, rapid response to emergencies, efficiency assessment of design solutions , identification of sources of potential risks, and forecasting of situation development considering historical data (Ivanov et al., 2020). Application of digital twins ranges from manufacturing, health, oil, refinery management, supply chain, and physical infrastructure including city planning (Barn, 2022).

In the context of digital twins connected to cities, referred to as the digital city twin, it can support data-driven urban planning and policy decisions by combining simulation, visualisation, and data analytics (White et al., 2021). They can be used in scenario development processes and testing scenarios before changes are implemented (Dembski et al., 2020). Digital city twins should be understood as sociotechnical systems that need to be understandable for all stakeholders (Nochta et al., 2021). White et al. (2021) describes how digital twins are used to create smart cities. The authors explain how data are generated from a wide variety of activities in the city, such as traffic and transportation, power generation, utilities, water supply, and waste management. Smart cities can then use the data to improve the mobility, environment, living standards, and governance of the city. To enable the improvements from the data, the digital twins are created through AI, data analytics, and ML. The digital twin is used to simulate options before taking physical action in the real world to identify strengths and weaknesses of each plan (White et al., 2021)

2.4 Combining Edge AI and Digital Twins

When combining Edge AI and digital twins, Edge computing can function as a local processing layer between the IoT devices in the physical layer and the central digital twin system, by moving computation closer to the data source (Knebel et al., 2023). The produced data from IoT devices can be processed close to where it is generated due to Edge AI (Singh & Gill, 2023). Thereafter, the processed outcomes can be sent to the central digital twin system that can support simulation, visualisation, and decision-support (Knebel et al., 2023).

Gupta (2025) has analysed how Edge AI and digital twin technologies are changing the industrial systems. The study shows that these technologies have the possibility to change to intelligent, real-time, and resilient operations. When using these technologies together, they can contribute to some of the most important issues, including system reliability, operational efficiency, scalability, and cybersecurity. When combining Edge AI with digital twins, an additional advantage includes energy efficiency and cost optimisation, due to local processing of data will reduce the amount of raw data that needs to be transferred to the cloud (Gupta, 2025).

However, the combination of Edge AI and digital twins introduces implementation challenges. The challenges connected to Edge AI include computing resources, network access, and data confidentiality and security (Singh & Gill, 2023). In digital twin implementation, edge computing can lead to constraints regarding latency, cloud traffic, system integration, and security (Knebel et al., 2023).

2.5 NexTArc and Use Case 1

Next Generation Open Innovations in Trustworthy Embedded AI Architectures (NexTArc) is an EU-funded research project that aims to accelerate the adoption of trustworthy, low-power, and secure Edge AI and IoT technologies across urban and industrial environments. The NexTArc project targets three use cases, including sustainable neighbourhoods, transparent industry, and eco-friendly mobility, linking people, places and production (European Commission, 2025).

This case study is delimited to the first use case (UC1), which focuses on developing a smart, sustainable, and livable urban district. UC1 is inspired by the digital city twin concept and seeks to develop a district-level digital twin for the Marieberg district in Stockholm. It is inspired by the digital city twin approach and aspires to provide powerful tools for urban planners and policymakers to visualise, simulate, and optimise various aspects of city life (NexTArc, 2025).

UC1 intends to integrate real-time data integration, immersive visualisation, and advanced analytics algorithms to evaluate predictive insights on future urban dynamics, and scenario simulation. The use case considers several main application areas, including energy-efficient building management integrated with district infrastructure, electric vehicle charging and logistics planning, mobility analysis based on traffic and people movement monitoring and noise mapping, sustainable food production through vertical farming and circular supply chains, and strategies to enhance citizen wellbeing by mitigating noise pollution (NexTArc, 2025).

UC1 is anchored in real-world challenges and has potential to be an instrument to reach the goals for a climate-neutral Stockholm 2030, through optimisation and visualisation of resources and assets. Its goal is to create a digitally efficient city twin to balance a system at the city district level. Its location is Marieberg, chosen as it has many challenges that many cities around the world try to meet. These challenges include well-planned mobility services for the commuters, logistics for foods and other products, long-term transportation infrastructure investments, short- to middle-term smart energy planning at building and district level, access to healthy food, and improving the wellbeing of all citizens (NexTArc, 2025).

Cicor (previously NEP) is a qualified partnering firm as it offers an AI platform optimised for ML on Edge devices. Their rich history in industrial technology ensures the platform's adaptability and robustness. Cicor works with crafting a dependable digital twin for UC1. Cicor is working with the technology requirements part, and will shape the high-level system designs based on stakeholders insights, optimising AI models through advanced data strategies, and the visual factors that may improve the explainability of AI algorithms. Sweco is the leader for UC1, and will focus on perspectives to support the implementation of digital city twins which will be central for UC1 (NexTArc, 2025).

3. Theoretical Framework

The following section presents the theoretical framework needed for the thesis. First, it presents implementation in sociotechnical systems, and then the Technology-Organisation-Environment (TOE) framework.

3.1 Implementation in Sociotechnical Systems

The theory of the sociotechnical systems is based on the principle that the development of a system needs consideration of both social and technical aspects, since these are two aspects in a complex system (Abdelmegid et al., 2024). Sittig and Singh (2010) present that a sociotechnical perspective highlights that information systems are shaped by the interaction between technical infrastructure, people, workflows, organisational structures, and external rules. Requirements of a sociotechnical system include hardware, software, personal, and community aspects (Barn, 2022).

The sociotechnical perspective highlights that the development of digital twins should not only focus on technical accuracy, but also how the system can be useful, understandable, and applicable in decision-making processes. The purely technological focus overlooks the necessity and costs of individual and organisational aspects of decision-making (Nochta et al., 2021). AI is one of the developing technologies that must be seen in a larger sociotechnical system (Salwei & Carayon, 2022). Barn (2022) describes digital twins from a sociotechnical perspective as a systems of systems and emphasises the relationship between a real-world system with a partial virtual representation.

3.2 Technology-Organisation-Environment Framework

The Technology-Organisation-Environment (TOE) framework was first introduced by Tornatzky and Fleischer (1990). It is an organisation-level theory that argues that three different elements of a firm’s context influence adoption decisions (Baker, 2011). The adoption decision refers to going from not having the innovation to formally adopting it (Tornatzky & Fleischer, 1990). In this context, it denotes the stage at which the innovation has been developed to a level of readiness that enables implementation and usage. The three elements are the technological, organisational and environmental contexts, that all three influence technological innovation (Baker, 2011; Tornatzky & Fleischer, 1990). The framework explains the context in which the innovation takes place, both internal in the organisation, and how the external environment affects where the innovation takes place (Tornatzky & Fleischer, 1990). The framework has a broad applicability and can provide explanation across a number of technological, industrial, and national/cultural contexts (Baker, 2011). Figure 1 shows the Technology-Organisation-Environment (TOE) framework.

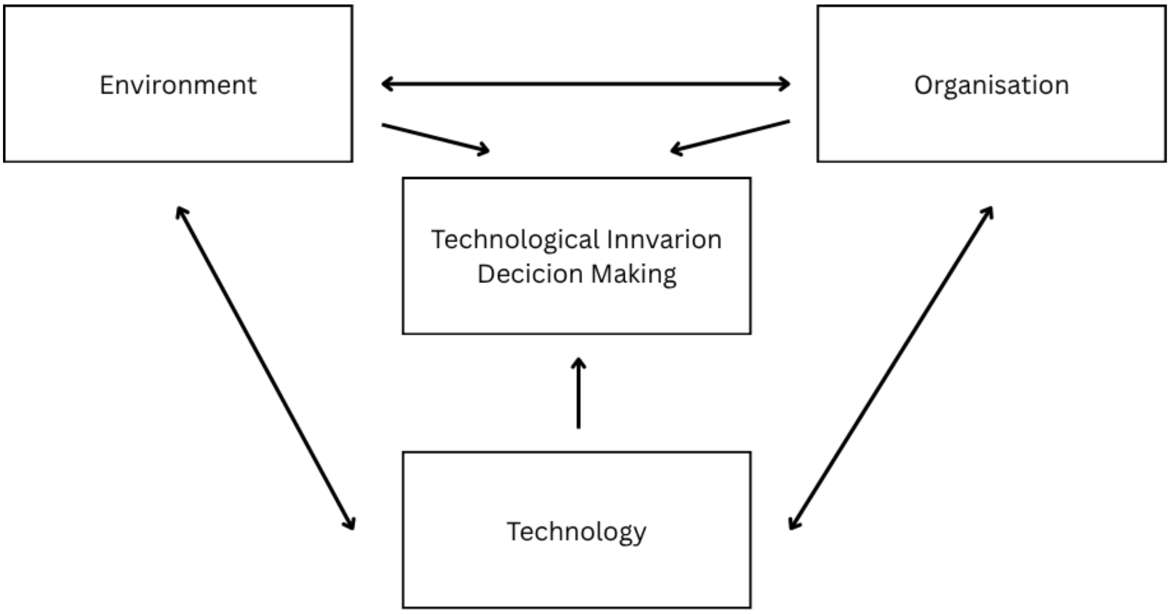

Figure 1. Technology-Organisation-Environment (TOE) framework

3.2.1 The Technological Context

The technological context includes all technologies that are relevant for the organisation, both internal and external technologies (Tornatzky & Fleischer, 1990). The internal technology includes all technologies the organisation has already implemented. The internal technology is important as it sets boundaries for the scope and pace of the technical change an organisation can undertake (Collins et al., 1988). The external technologies consist of all available technologies external to the organisation (Tornatzky & Fleischer, 1990). The authors propose that different organisations have different technical opportunities, since not all innovations are relevant across industries.

Innovations that exist outside of the organisation are divided into three types depending on the implication of adoption. These three types are those that create incremental, synthetic, or discontinuous change (Baker, 2011). Innovations that create incremental change provide new features or enhancements to existing technology (Tornatzky & Fleischer, 1990). These innovations represent the least amount of risk and change for the organisation (Baker, 2011). Innovations creating synthetic change represent a middle point of moderate change, involving the combination of existing technologies to create new products or processes. Innovations that produce a discontinuous change represent the development of significant new products of processes (Tornatzky & Fleischer, 1990). The discontinuous change requires the organisation to make quick and decisive adoption decisions to maintain and enhance competitive standing (Baker, 2011). As these technologies often qualify as pioneering there is a high risk in their use and implementation (Tornatzky & Fleischer, 1990).

3.2.2 The Organisational Context

The organisational context is characterised in terms of a number of descriptive measures, such as firm size, the centralisation, formalisation, complexity of its managerial structure, quality of human resources, and the amount of slack resources available (Tornatzky & Fleischer, 1990). Tornatzky and Fleischer (1990) suggests that organic structures of the organisations were highly associated with more successful introduction of innovation. Organic structures are characterised by lateral communication, decentralised leadership and control, and a high degree of networking between people and units. It is also shown that centralisation is connected to innovation. Centralisation refers to the concentration of decision making activity and power. Tornatzky and Fleischer (1990) argues that the more power is decentralised the more innovative the organisation is likely to be. Previous research suggests that structural characteristics such as complexity, formalisation, and centralisation are related to innovation, but it is uncertain how the characteristics affect innovation and to what extent. Baker (2011) shows that decentralised and organic organisational structures are better for the adoption phase, while more centralised structures are best suited for the implementation phase.

Other factors that are important for innovation in an organisation are informal linkage, communication, and top management strategic behavior. Informal linkages are described as informal linking agents, explained as teams and employees that have informal links to between departments of other value chain partners (Baker, 2011). Informal linking agents are important for adoption of innovation as they both serve as a communication function, but also provide the energy and labor necessary for implementation activities. Other than that, they act as bridges between different phases of the decision process for technological innovation. Top management leadership behaviours include planning and communication for change, and developing directions that support innovation (Tornatzky & Fleischer, 1990). Top management can foster innovation by creating an organisational climate that supports innovation (Baker, 2011).

Furthermore, organisation slack and size are two factors that have the possibility to affect the adoption and development of innovation (Tornatzky & Fleischer, 1990). Slack resources refers to the amount of resources exceeding what is needed to maintain fundamental activities (Cyert & March, 1963). Slack resources are shown to be necessary for innovation, but do not always lead to technical innovation. The organisation size is shown to be the most explanatory variable for development of innovation (Tornatzky & Fleischer, 1990). Studies have shown that bigger organisations implement innovations more often than smaller organisations. However, regarding size, there is no conclusive link between size and innovation. Larger organisations are generally more likely to adopt innovations, but it can be caused by other underlying organisational factors (Baker, 2011). Organisation size functions as an indirect measure of more meaningful underlying factors, such as access to resources, rather than as a direct indicator of hierarchy, complexity, or decision-making (Tornatzky & Fleischer, 1990).

3.2.3 The Environmental Context

The environmental context includes the structure of the industry, the presence or absence of technology service providers, and the regulatory environment. With regard to industry life cycles, organisations in rapidly growing industries tend to innovate more rapidly. In mature or declining industries, the implementation of innovations can vary. Some organisations use the incline of an industry to innovate through efficiency initiatives or by expanding into new lines of business. Other organisations avoid investments in innovation to minimise costs. Another affecting factor is the governmental regulations, it can have both beneficial or harmful effects on innovation. Regulatory requirements may stimulate innovation by mandating new solutions, but strict safety, testing, or privacy roles may also slow innovation by making it more costly and less flexible (Baker, 2011).

The environmental context refers to the environment in which the organisation operates. How the environment affects the organisation depends on several factors, including industry, competitors, access to resources supplied by others, and dealings with the government. These factors present both constraints and opportunities for technological innovation (Tornatzky & Fleischer, 1990). Tornatzky and Fleischer (1990) argues that organisations within the same industry tend to be exposed to similar problems and opportunities. The authors have found some general conclusions regarding affecting environmental factors. The first of these factors are firm size, concluding that larger firms tend to use more types of technology and to be earlier adopters of technology. The reason appears to be that large firms can be more likely to have the capital to invest in new equipment, and large firms might be involved in a greater variety of production activities leading to greater possibility to find applicable technology. Another affecting factor is intensity of competition, measured using market concentration as an indicator. Tornatzky & Fleischer (1990) describes that previous studies show that more intense competition leads to higher adoptions rates. They also argue that market uncertainty has the possibility to affect innovation for an organisation. It is argued that some organisations seek out innovation to manage uncertainty, while others may hold on to available resources to avoid risk.

4. Related Work

The following section presents related work for the study, and is divided into technological and theoretical related work.

4.1 Related Work on Digital Twins and Edge AI

Kreuzer et al. (2024) analyses artificial intelligence within digital twins through a systematic literature review. The authors describe digital twins as virtual replicas of real-world systems that accurately reflect the system's behaviour. A digital twin is characterised by a physical-to-virtual connection, as well as a virtual-to-physical connection. This entails that there is a data stream that replicates the real world, as well as physical changes due to the output of the digital twin. This study investigates literature examining the intersection of digital twins and AI, to give an overview of the state of the field of research. The study concludes that AI components can fulfill a variety of tasks within a digital twin. Digital twins with an AI component have the possibility to perform a wide range of tasks which require predictive functionality. The study also concluded how the bidirectional link between physical and virtual systems is shown in previous literature. Most studies rely on historical data with limited implementation of live data flows and functional feedback loops. Therefore, the majority of proposed digital twins lack full bidirectional integration in practice (Kreuzer et al., 2024).

Rahman et al. (2025) examines how ML is applied to industrial automation and how it is enhanced through the integration of digital twins and Edge AI. The study uses a systematic literature review of recent studies to analyse ML applications across three domains, including predictive maintenance, quality control, and process optimisation. The review shows that Edge AI enables low-latency, autonomous decision-making close to the physical systems, while digital twins support simulation, validation, and closed-loop optimisation. The study concludes that combining ML with Edge AI and digital twins improves scalability, responsiveness, and resilience in industrial settings. It also revealed challenges related to system integration, hardware constraints, and standardisation, which are relevant to the implementation of Edge AI and digital twins (Rahman et al., 2025).

Kritzinger et al. (2018) aims to provide a categorisation of the different contributions related to digital twins, highlighting the lack of consistent definition across studies. The study is a categorical literature review, reviewing 43 separate studies. The categorisation proposed is based on the level of data integration, their focused area, and the technology used. The categories are digital model, digital shadow and digital twin, where digital twin represents a full bidirectional data exchange in real time. Their findings show that there are no common definitions of digital twins, and that the term is used synonymously with digital model and digital shadow. Therefore, the study highlights the need for clearer definitions and more empirical research on the subject (Kritzinger et al., 2018).

4.2 Related Work on TOE and AI Implementation

Hughes et al. (2026) studies the underlying technological, organisational and environmental focused factors that influence the use of generative AI within organisations. The study is conducted based on the Technology-Organisation-Environment (TOE) framework. The approach for the study consisted of both a qualitative and quantitative phase, to be able to get insight of the complexity and multidimension of adoption of generative AI. The qualitative phase consists of interviews to get in-depth insight from organisational stakeholders. The quantitative phase consists of a comprehensive survey to test the key associations identified in the qualitative phase. The participants in the study consisted of mid-level managers from organisations that already use generative AI and decisions-makers from multiple organisations worldwide. The study concludes that the technological and organisational factors are the most affecting drivers of generative AI use, while the environmental factor does not affect as much. Within the technological context, the complexity, particularly explainability and trust in outputs, acts as a significant barrier. Within the organisational context, staff skills and organisational change capacity acts as drivers. While within the environmental context, regulatory pressure has not significantly influenced adoption of generative AI (Hughes et al., 2026).

Gama and Magistretti (2025) conduct a literature review of 62 empirical studies to summarise the role of AI in influencing innovation capability based on empirical studies. The study uses the TOE framework to structure the analysis of factors influencing the adoption of AI in innovation management. Innovation management is described through the definition of innovation capabilities, which is defined as “skills and knowledge needed to effectively absorb, master and improve existing technologies, and to create new ones” (Gama & Magistretti, 2025, p. 77) The TOE framework is used to categorise existing research into three contextual dimensions, technological, organisational and environmental. The technological factor includes AI capabilities and technical characteristics of AI. The organisational factor includes internal structures, resources, and managerial aspects. The environmental factor includes market and competitive conditions. The study shows that AI adoption in innovation management is influenced by a combination of these three factors rather than by technological factors alone (Gama & Magistretti, 2025).

5. Methodology

The section below presents the methodology that is used to conduct the study. It is divided into research design, data collection, data analysis, ethical considerations and trustworthiness of a qualitative study.

5.1 Research Design

The following section describes the research design for the study. It describes the choice of research method, the context of the study and the research approach.

5.1.1 Qualitative Method

When conducting a study with a specific aim, the first step is choosing the research method for the study, whether to do a quantitative or qualitative study. A quantitative study has a focus on numbers and has a scientific focus when retrieving data, with the main methods being questionnaires and surveys, quantitative content analysis, secondary data analysis and structured observations. On the other hand, qualitative research aims to generate deep insights concerning a specific topic, and is conducted through engagement with places and social actors (Clark et al., 2021). Common methods for collecting qualitative data are through interviews and focus groups, as it allows researchers to explore participants' views, experiences, and motivations in depth (Gill et al., 2008). As this study aims to answer in-depth questions and to obtain a broad understanding of a phenomenon a qualitative research method is chosen.

5.1.2 Thematic Analysis

Thematic analysis is a research method used to identify and interpret patterns or themes in a data set, which often lead to new insights. It involves identification of patterns in a data set, which are then used to understand their meaning in the context of the research (Naeem et al., 2023). Thematic analysis is both systematic and flexible when analysing qualitative data. It is systematic as it provides a consistent and logical way to analyse the data leading to rich descriptions and in-depth explanations. Although, it is flexible as it is not tied to a particular research philosophy (Saunders et al., 2023).

When conducting a thematic analysis it is important to know what a theme is and how to obtain them. According to Braun and Clarke (2006) a theme represents a patterned response of meaning within the data set that has importance in relation to the research questions. There is no clear answer of what proportion of the data needs to display evidence of the theme to be considered a theme. Therefore, the judgement of the researcher is necessary to determine what is considered to be a theme. It does not necessarily depend on quantifiable measures, rather if it captures something important in relation to the research questions (Braun & Clarke, 2006).

Naeem et al. (2023) has divided the thematic analysis into six clear steps. The initial step contains transcription and the selection of quotations. It is used to discern initial themes and important sections, to select quotes to represent viewpoints and patterns to the research objectives. The second step consists of selection of keywords, to identify recurring patterns and terms to use as keywords. The third step is coding of data, where short phrases or words are assigned to segments of data that capture the core message, significance, or theme of the data. The fourth step is theme development, which involves organising codes into meaningful groups to identify patterns and relationships. These themes are created to identify patterned meanings that link the research questions and data. The fifth step is conceptualisation through interpretation of keywords, codes, and themes. This step involves understanding and defining concepts emerging from the data. The sixth and final step is development of the conceptual model, which involves creating a unique representation of the data and is often connected with existing theory. The created model serves to answer the research questions and to be used for the study's contribution to knowledge (Naeem et al., 2023). The conceptual model does not necessarily lead to the creation of a new theory, it can likewise be a representation in visual format of how a system or idea works or is combined. The conceptual model may be constructed by the themes that emerged from the thematic analysis, providing a significant outcome of a qualitative study (Christou, 2023).

5.1.3 Case Study

There is no standard definition of a case study. Benbasat et al. (1987) define a case study as an approach that examines a phenomenon in its natural setting, collecting data to develop a comprehensive understanding based on one or a few entities. Gerring (2007) defines a case study as an in-depth analysis of a single case to be able to generate insights that can be applied to a broader class of similar cases. Case studies are useful when the subject of study is broad, and therefore an in-depth investigation is needed, and the subject cannot be studied outside the context it occurs in (Dubé & Paré, 2003).

According to Benbasat et al. (1987), there are three main reasons to conduct a case study. First, it provides the possibility to study the case in its natural habitat. Second, the study allows the possibility to answer 'how' and 'why' questions, and to be able to answer more complex research questions. Third, the case study approach is suitable in areas with a few previous studies (Benbasat et al., 1987).

Case studies have been criticised as it is discussed whether the results can be generalised, as the empirical findings are related to a specific context in which the study is conducted (Tsang, 2014). However, it is also discussed whether case studies should be evaluated based on their ability to produce generalisable findings. Thomas (2011) argues that the strength in case studies is its possibility to provide in-depth, context-dependent insights, which support further understanding of a subject. Stake (1978) introduces the concept of naturalistic generalisability, which is developed within the reader when recognising similarities between the case and their own experience.

5.1.4 Abductive Research Approach

It is important to decide which research approach to use, deductive, inductive or abductive approach, depending on what the study aims to examine. A deductive approach proceeds from relevant theory in order to formulate hypotheses, to then be tested empirically in the study (Clark et al., 2021). The inductive approach works the other way around, the theory is the outcome of research and is formed by generalisable outcomes of observations (Clark et al., 2021). Another possible approach is an abductive approach, meaning deduction and induction together (Clark et al., 2021). The abductive approach is a combination of deduction and induction, and is developed through a mixture of established theoretical models and new concepts derived from observations (Dubois & Gadde 2002). In this study, an abductive approach is chosen, as it is grounded in the TOE framework but goes back and forth between the theoretical framework and the empirical findings.

Thematic analysis can be used despite the research approach. When using a deductive approach, the themes analysed are linked to existing theory, so the examination of themes will be more focused on parts of the data rather than seeking to analyse it all. When using an inductive approach, the themes will be entirely derived from the data, which will not be based on existing theory. As this study uses an abductive approach a combination of these approaches will be used, creating themes from the data while allowing theoretical concepts to inform the interpretation and refinement of existing themes (Saunders et al., 2023).

5.2 Data Collection

The section below explains how the data were collected to conduct the study.

5.2.1 Semi-structured Interviews

The purpose of conducting interviews is to understand other people's points of view, to understand the perspective of an individual (Kvale, 1996). Interviewing, as a qualitative research technique, is considered an effective and powerful data collection technique in social studies. The interview must be well prepared by the researcher to be effective (Dursun, 2023).

When choosing to have interviews as the qualitative research technique, it is important to be aware of the strengths and weaknesses of the method. The first strength of interviews is that during the interview process, the researcher can collect as detailed data as possible, and there is no delay between question and answer. Another strength is that the researcher can give immediate feedback to the data received during the interview, and complex instructions can be explained by the researcher. But there are also weaknesses to be aware of when conducting interviews. Interviews can be time consuming and costly for the researcher. Another weakness is that the information can be misunderstood, which may affect the reliability of the research (Dursun, 2023).

The types of interviews can be divided into three different types, structured, semi-structured and unstructured. The unstructured interviews include the least amount of structure, and the researcher determines the interview questions from the initial base line, but can also produce new questions according to the flow of the interview (Dursun, 2023). It leads to the interviewer having to develop, adapt, and generate follow-up questions to reflect the purpose of the research. It proceeds from the assumption that the interviewers do not know in advance all the necessary questions (Qu & Dumay, 2011). These types of interviews are primarily used in ethnography, participant observation and case studies (Dursun, 2023). The structured interviews contain preprepared questions and the participants are expected to give answers from a limited number of response categories or short answers with little flexibility (Dursun, 2023). This leads to very little flexibility in the interview approach as it has clear instructions and short answers. A concern with this type of interviews is that the researchers have an affecting role in the creation of the question design, which can affect the data collected. Thus, there are standardized procedures to reduce the probability of the results being influenced by the interviewers bias (Qu & Dumay, 2011). These are primarily used to obtain demographic data (Dursun, 2023). The semi-structured interview is more flexible than the structured interview form. The researcher is able to ask different questions according to the flow of the interview, which gives a possibility to obtain more detailed information. This is the type of interview that is frequently preferred by researchers (Dursun, 2023). Another advantage is that the semi-structured interview allows researchers to disclose important and often hidden facts of behaviour, which makes it a convenient way of gathering information (Qu & Dumay, 2011).

5.2.2 Selection of Participants

When gathering data through interviews, it is important to identify which participants to choose. It depends on what the study aims to identify and from whose point of view the information is intended to be evaluated. To select participants for the semi-structured interviews, purposive sampling can be used, which means selecting participants relevant for the research questions (Bell et al., 2022). According to purposive sampling, participants are chosen on the basis of the information they can provide in a certain field (Clark et al., 2021). The findings may be applicable to participants with similar characteristics (Dursun, 2023). Therefore, when selecting participants it is important to choose participants that are representative of the people affected by the study, in this case within NexTArc.

Determining the appropriate number of participants in a qualitative study is challenging. It depends on the aim of the study, the complexity of the phenomenon, and the degree of homogeneity within the sample (Guest et al., 2006). The number of participants is determined by the point at which data saturation is reached. Data saturation is considered to be reached when no new themes or insights emerge from additional interviews (Fusch & Ness, 2015).

5.3 Ethical Considerations

When conducting qualitative research it is important to consider the ethical considerations, due to the in-depth interaction with researchers and participants. Researchers must therefore consider how participants are informed, how their voluntary participation is ensured, and how their identities and responses are protected throughout the research process (Arifin, 2018). Orb et al. (2001) describes this through the principles autonomy, beneficence and justice. Autonomy implies that participants should be informed about the study, participate voluntarily, and have the right to withdraw from the study. Beneficence describes that the researcher should minimise potential harm and use the empirical findings carefully. Justice implies that participants and their contribution should be treated fairly.

In qualitative research, informed consent, anonymity, and confidentiality are central considerations. Informed consent highlights the importance of informing the participants which data will be collected and how it will be used. Regarding anonymity and confidentiality, it means that the researcher should avoid presenting information that could identify participants and only presenting the information needed for the research (Sanjari et al., 2014). Confidentiality is challenging as detailed descriptions of participants and their contexts has the possibility to make individuals identifiable even when names are removed. Kaiser (2009) argues that the researcher must consider how the empirical findings are presented, and that confidentiality should be handled carefully throughout the research process.

5.4 Trustworthiness of a Qualitative Study

When conducting a qualitative study, it is important to evaluate the quality of the study and its results. To examine the trustworthiness of the study, Lincoln and Guba's four criteria are considered, considering credibility, transferability, dependability and confirmability (Bryman, 2016; Shenton, 2004). These four criteria are used because the traditional concepts of validity and reliability are considered difficult to directly apply or translate from quantitative to qualitative research contexts. (Shenton, 2004).

The first criterion, credibility, seeks to ensure that the study tests what is intended, and that it accurately represents the participants' experiences (Bryman, 2016; Shenton, 2004).

Credibility can be strengthened by using established research methods, using iterative questioning, and the use of triangulation (Bryman, 2016; Shenton, 2004). Credibility is therefore concerned by showing that the findings are consistent with the empirical material.

Transferability concerns the extent to which the findings can be applied to other contexts, also connected to generalisability (Bryman, 2016; Shenton, 2004). Shenton (2004) describes that the empirical findings are often limited to a number of individuals and environments, which means that it cannot be explained as generalisable results. Instead, the researcher should provide contextual information, which gives the reader the ability to assess whether the findings can be transferred to another setting. This can be supported by describing the participants and organisations involved, the data collection methods, and including other relevant information (Shenton, 2004).

Dependability concerns whether the research process is described in enough detail for another researcher to understand how the study was conducted. Shenton (2004) explains the difficulty to ensure that the empirical findings would be the same if repeated, as qualitative research is tied to the social context. However, this can be strengthened by explaining the research process in detail, with as full transparency as possible.

Confirmability concerns how well the findings are based on the participants' experiences rather than the researcher’s assumptions. This can be strengthened through a detailed methodological description, in which all decisions and assumptions are clearly described (Bryman, 2016; Shenton, 2004). This leads to all assumptions and decisions made being transparent and easy for the reader to follow.

6. The Study

The following section explains how the research was conducted. It is an explanation of the development of the research in relation to the methodology.

6.1 Case Context

This study was conducted through a case study of the EU-funded NexTArc project, focusing on Use Case 1. The case was selected because it represents a complex sociotechnical setting in which digital twins and Edge AI are developed. The project is developed through collaboration between several organisations with different technological and organisational competences. Therefore, it provides a relevant context to examine the aim of the study. A case study approach is considered appropriate for this research as the study aims to contribute with in-depth understanding of the technical and organisational factors for the NexTArc project. As the NexTArc project includes complex interactions between technical and organisational factors within a specific real-world context, it makes it difficult to apply more controlled research methods.

Use Case 1 focuses on the development of a digital twin for the Marieberg district in Stockholm. It seeks to develop a district-level digital twin, and is planned to provide tools to visualise, simulate, and optimise aspects in the district. The use case plans to integrate real-time data integration, visualisation, and using advanced algorithms to evaluate insights of future urban dynamics and simulation. It depends on data infrastructure, Edge AI processing, system integration, user interfaces, and collaboration between actors. The study is delimited to Use Case 1 as it creates a clear empirical boundary, while allowing an in-depth analysis of the project.

6.2 Development of the Interview Script

The interview script was developed based on the purpose of the study and the theoretical framework. As the study aims to analyse the technological and organisational factors and how they affect the development and implementation of digital twins and Edge AI, the interview questions were designed to capture both practical experiences and more reflective perspectives from participants. Other than that, the interview script also included questions capturing the technological, organisational, and environmental factors to enable successful implementation and integration of digital twins and Edge AI.

A semi-structured interview format was chosen because this approach makes it possible to pursue a clearly defined purpose while allowing participants the flexibility to elaborate with their perspectives, interests within the scope of the study. This choice of methodology allows a balance between consistency and openness, ensuring that the key themes are explored while still providing space for unanticipated insights to be included. The script of the interviews was developed to align with the overall aims of the study and to effectively address the research questions. It was designed to collect relevant and nuanced data by prompting participants to engage with central topics, while also allowing follow-up questions and deeper exploration when appropriate.

The interview script was created based on the three contexts of the TOE framework, ensuring the theoretically informed structure for the data collection. The script was divided into three main sections, technological factors, organisational factors, and environmental factors, each including a set of questions designed to capture relevant information within these factors. The structure enabled a thorough exploration of the factors affecting the phenomenon of the study. The questions in the interview script were created with regard to the study's research questions, emphasising their alignment with the TOE framework. The TOE framework was used to create the baseline of the interview script to ensure that the technological, organisational, and environmental factors were all covered. However, the script was not used as a strict checklist. Follow-up questions were asked when participants introduced topics that were specifically relevant for the study. In this way, the interview script supported an abductive research approach, as the empirical data was allowed to develop new insights while still being interpreted in relation to the theoretical framework. The interview script used in the semi-structured interview can be found in Appendix A: Interview script.

6.3 Participants and Sampling

The selection of participants in this study was conducted to be able to obtain relevant insights into the development and implementation of digital twins and Edge AI. The participants were selected based on their involvement in the project and their experience with the technical and organisational aspects within the project. To capture a range of perspectives for the width of the project, participants were chosen from different roles and different organisations involved in the project. This reflects the range and complexity of the project, and makes it possible to include all aspects. The selection criteria required included that the participants had direct or indirect experience with the development, implementation, or integration of digital twins or Edge AI solutions within the project. This ensured that all participants could provide relevant insights related to the aim of the study.

The participants were anonymised in the thesis and are presented as Participant A to Participant J. This choice was made to reduce the risk that statements would be able to be connected to specific people. Since the project involves several organisations and the interviews contain reflections on collaboration, expectations, and challenges, anonymisation was chosen for ethical and analytical reasons. The organisations for each participant were not used as a categorisation in the analysis. Instead, the participant's roles and contributions to the development and integration process were the main categories.

The number of participants was not predetermined in detail but based on the principle of data saturation. Interviews were conducted until no new themes of significant information emerged from the data, indicating that adequate depth and variation had been achieved. To structure the analysis and ensure comparability between responses, the participants were categorised based on their professional roles, differentiating between project leaders and developers. This enabled the study to examine possible differences in insights and perspectives between roles within the development and implementation of Edge AI and digital twins. The final sample consisted of ten participants. After the final interviews, the empirical findings showed recurring patterns. Since additional interviews were not expected to generate valuable new themes in relation to the aim of the study, the sample was considered sufficient for the purpose of the study. Table 1 shows the participants interviewed, including role, date, time consumption, interview medium, and language.

Table 1. The participants in the interviews

	Role	Date	Time consumption	Interview medium	Language
A	Project leader	2026-03-11	30 min	Microsoft Teams	Swedish
B	Project leader	2026-03-13	45 min	In office	Swedish
C	Developer	2026-03-13	40 min	In office	Swedish
D	Project leader	2026-03-09	45 min	Microsoft Teams	Swedish
E	Developer	2026-03-31	35 min	Microsoft Teams	English
F	Developer	2026-03-31	35 min	Microsoft Teams	English
G	Developer	2026-05-05	35 min	In office	Swedish
H	Developer	2026-05-05	30 min	In office	Swedish
I	Developer	2026-05-07	35 min	Microsoft Teams	Swedish
J	Project leader	2026-05-11	40 min	Microsoft Teams	Swedish

6.4 Conducting the interviews

The interviews were conducted between March and May 2026. They were held either through Microsoft Teams or in person, depending on availability and location of the participant. The duration of the interviews ranged from 30 to 45 minutes. The format of the interviews made it possible to include participants from different organisations and locations while still maintaining a similar structure across all interviews. Before each interview, verbal informed consent was obtained from the participant before the interview was conducted.

Each interview started with an introduction of the purpose of the study and the focus on digital twins, Edge AI, and NexTArc Use Case 1. Following this, the participants were asked introductory questions about their role and involvement in the NexTArc project. Then the interview followed with the thematic structure of the interview script. However, the order of the questions was adapted when needed depending on the participants' answers, in order to maintain the natural flow in the interview. The semi-structured format made it possible to capture differences between participants, as well as participant's own interpretations, experiences, and examples. Some of the participants focused on the technological factors, while others on the more organisational and environmental factors.

The interviews were later transcribed and prepared for analysis. As the majority of the interviews were conducted in Swedish, therefore significant quotations and summaries were translated into English for the thesis. The translation was made with the aim of preserving the meaning of the statements rather than achieving a word-for-word translation. This was done to make the empirical material consistent with the language of the thesis while still maintaining the intended meaning of the responses.

6.5 Application of the Thematic Analysis

The thematic analysis followed six steps. The analysis was conducted abductively, meaning the coding and theme development were based on both the empirical findings and the theoretical framework. The TOE framework provided an initial structure for understanding the technological, organisational, and environmental factors, while the empirical data identified the most important themes in the NexTArc case.

The first step consisted of review of the interview transcripts, and relevant quotations and sections were selected. The selection of sections was based on their connection to relevant information regarding how participants understood digital twins and Edge AI, what they considered important for the development and implementation, and the success factors and challenges they have observed. After this step, the empirical foundation for the analysis was created. In the second step, keywords were identified from the empirical findings. These keywords were useful as they showed recurring patterns across several interviews and were used to implement structure for the analysis. The third step consisted of developing codes from the keywords and selected statements. These codes were short analytical labels that captured the core meaning of parts of the data. This step transformed the interview material to more feasible analytical units. In the fourth step, codes were grouped into broader themes. The themes are created to identify patterned meanings that link the empirical findings to the aim of the study. In the fifth step, the themes were analysed in relation to the research questions and the theoretical framework. Each theme was examined whether it primarily concerned technological, organisational, or environmental factors. It was also recognised if there were themes that overlapped over multiple factors. The sixth and final step consists of using themes to develop the conceptual model. The purpose was to provide a clear representation of how the most important findings identified in the analysis relate to each other, and therefore not to generate a new theory. The themes were treated as connecting parts of the development and implementation process. The analysis was therefore focused on how technological, organisational, and environmental factors interact and affect the development and implementation of digital twins and Edge AI in NexTArc.

6.6 Measures Taken to Ensure Research Quality

Several measures were used to ensure the quality and trustworthiness of the study. Given that the thesis is based on qualitative research, the study was evaluated based on the criteria of credibility, transferability, dependability, and confirmability.

Credibility was addressed by the selection of participants. All participants chosen had relevant knowledge of NexTArc, digital twins, Edge AI, or the organisational collaboration. The interview script was also designed to align with the aim of the study and the TOE framework, which ensured that the interviews generated relevant information for the study. Transferability was checked by providing a detailed description of the case context, the participants, the sampling process, and the analytical procedure. The aim of the study was not to reach statistical generalisation, as it is a single case study. Instead, it provides insights depending on context that may be useful for similar projects. By making the context of the case clear, readers can assess whether the findings are relevant for other projects or organisations. Dependability was enhanced by following a clear research process. Throughout the study, it used a defined interview script, a clear participant selection, and a structured thematic analysis process. Throughout the process of the study, all decisions and results are transparent and showed all steps to understand how the findings were produced. Confirmability was addressed by explaining the difference between empirical findings and analysis as clearly as possible. The results section presents participant perspectives, while the analysis section analyses the results through the TOE framework. Furthermore, the abductive approach was used by allowing the empirical findings to emerge from the data while using the TOE framework as an analytical perspective rather than constricting the results to a fixed framework.

Another considered aspect during the analysis was researcher bias. There is always a risk that certain statements are more emphasised than others. This is due to it being the researcher that interprets the interview material. To reduce the risk, the analysis focused on recurring patterns across several interviews. Important insights from participants were also included when they were directly relevant for the research. Transparency was strengthened by using participant labels which makes it possible to show where each finding came from.

Ethical considerations were taken into consideration in several ways. Before each interview, participants were informed about the purpose of the study, that participation was voluntary, and that they could withdraw from the interview at any time. Furthermore, verbal informed consent was obtained before the interview started. The interview material was used only for the purpose of this thesis, and details that could make individual participants or organisations identifiable were avoided or generalised when presenting the empirical findings. To treat the contributions of the participants fairly, the interviews followed the same overall structure, while still allowing participants to elaborate on issues most relevant to their role and experience. Ethical considerations were also taken into consideration through anonymisation and cautious handling of the interview material. Participants were presented through labels as Participant A to Participant J, and the analysis focused on roles and the data produced rather than personal identities.

6.7 Structure of the Results and Analysis

Since the NexTArc project is complex and involves several organisations, different roles, and many dimensions, the results and analysis are structured in several steps. The reason for this is to make the analytical process as clear as possible to show how the empirical material was interpreted.

Initially, the results section presents the interviews findings categorised by each participant. This structure was chosen to preserve the different perspectives of each participant, and to make clear where the information in the empirical findings came from. This leads to the result being a presentation of each participant's perspective before being interpreted.

The analysis is divided into themes from the thematic analysis and conceptualisation. The first part contains all themes that emerged from the thematic analysis based on the empirical findings. This analysis was conducted abductively, meaning the themes were developed from the empirical material while being interpreted through the TOE framework. The analysis then led to the second part, the conceptualisation. This part uses the main themes to show how the most important factors relate to each other. The findings were used to create a conceptual model which also is presented here. Finally, the discussion and conclusion section used the results and analysis to answer the aim of the study, as well as the research questions. It also discusses the theoretical and practical implications of the findings.

7. Results

This section presents the results from the interviews and the main points made. The names of the participants are anonymised. The citations are translated from Swedish, as most of the interviews were held in Swedish.

7.1 Participant A

Participant A provides an advisory perspective through engineering design and industrial architecture on digital twins, rather than direct involvement in the NexTArc project. The participant participates in discussions on digital twins and is interested in how they can support design processes. This makes the interview valuable because it connects NexTArc to a broader organisational setting around 3D modelling, and the transition from digital models to operational digital twins.

A main theme in the interview is that a digital twin is a lot more than a 3D model. Participant A describes digital twins as platforms for coordination, collaboration, clash detection, design review, documentation, and automation. In the participants' work, digital twins have the possibility to use and process data into a shared environment. From a technological perspective, this highlights the importance of the quality of the data, including data richness, interoperability, and the ability to integrate multiple data sources. Participant A defines the existence of a digital twin as "If there is a link between the data and reality, then you have a digital twin, provided that it is updated and synchronised with real events". This is directly relevant for NexTArc where the digital twin depends on data flows from buildings, sensors, and urban systems.

Participant A also emphasises the importance of reliability as a success factor, where uptime becomes critical. The participant refers to uptime as the amount of time that the digital twin platform is available and functioning when users need it. As the platform must be trustworthy to support daily work, uptime is an effective way to ensure the reliability of a digital twin. The participant explains that the value of the digital twin depends not only on functionality, but also on whether the platform is trusted by users. A challenge when developing a digital twin is measuring performance, as the entire digital twin rarely fails as a whole, instead individual, independent parts fail separately. Therefore, performance evaluation must account for modules failing rather than the whole system's uptime.

The interview also demonstrates an issue related to defining digital twins. The definition of digital twins, both within the project and in general terms, is not always consistent. Participant A is critical of calling any 3D scan or model a digital twin, when it actually is a static digital model. It is important to have a clear definition of digital twins as if not, collaboration between partners and expectations can be affected.

7.2 Participant B

Participant B contributes with a perspective on digital twins as systems that combine real-time data, databases, computation, and AI. The interview focuses on the technological aspects of digital twins and their importance for NexTArc.

A central theme in the interview is the information gap between physical hardware and higher-level users. Participant B sees a large distance between the hardware layer that produces data and the user-oriented layer that seeks to make the data useful for users. Participant B describes this as “a very large information gap between the user and the physical layer”. It makes clear that this information gap is both technological and organisational, as it concerns data structure and interfaces, as well as coordination between organisations with different roles and expertise. Participant B also notes that the digital twin can serve as an active model as commands can be sent back to the physical layer. This view is important for NexTArc, as the digital twin supports action and control.

The interview also discusses Edge AI, explained as smaller and simpler AI models running near the devices, while the system logic can exist both centrally and at the edge. Participant B explains the need for standardised ways to implement and develop models is a technological success factor. The participant also states that the NexTArc project is still in a proof-of-concept phase, so the goal is to demonstrate functionality using physical data. It is also stated that real data for testing is still missing, which makes it an implementation challenge at the time.

From an organisational perspective, Participant B identifies both potential and challenges. NexTArc is considered a good match for the organisation and gives them flexibility in the project. However, organisational challenges have also emerged, as it has been difficult to create a coherent view of what is expected and not all partners seem to be equally prepared to contribute. The challenge is mainly regarding project-level coordination and shared visibility. This interview contributes to the study by showing that digital twin and Edge AI implementation depends on information integration, model implementation, data availability, and the communication between partners.

7.3 Participant C

Participant C describes NexTArc from a technological perspective where the organisation is responsible for delivering capabilities for the use case. The interview contributes value because it combines a functional view of digital twins and gives concrete reflections on Edge AI, data access, and organisational dynamics of large EU projects.

During the interview, Participant C discusses uncertainty regarding how the digital twin is defined within NexTArc. The participant suggests several possible interpretations for digital twins, including a digital representation of physical elements, a simulation to test scenarios, or a 3D model enriched with sensor data. Digital twins are not only a single artefact, but a collection of components, data streams, models, and visualisations. This view supports a modular understanding of digital twin implementation, where different partners in the project contribute different layers. Participant C highlights data analysis, image analysis, and sensor data handling as central technological aspects. It is shown that digital twin development requires domain knowledge in addition to software compatibility.

Edge AI is described as a useful aspect as it allows processing of data to move closer to where it is generated. Participant C explains that images could be processed near cameras, which would avoid unnecessary data transfer. It is explained as “capture the images where they arise, close to the camera. Instead, the computation is moved to the data”. This aspect reflects various technological success factors, such as local processing capacity and the ability to run software on resource-limited devices. Developing the platforms in a new environment can take time, but the participant does not see this as a major project risk.

Participant C identifies organisational challenges as more significant than the technological challenges. The key factor is access to relevant data and edge devices. Participation in NexTArc is presented as valuable for the organisation, as it enables product development, technical broadening, and new relationships. The collaboration with the Swedish partners is described as working without issues, while international collaboration is seen as a valuable opportunity but constrained by budget and scope. The participant explains that collaboration mostly emerges gradually through interactions with partners. In summary, the interview shows that implementation success depends on technical platform readiness, access to data and devices, flexible scoping, and networking across the partner network.

7.4 Participant D

Participant D provides a project management and data-integration perspective. The interview is relevant to the technical and organisational factors as it focuses on real-time data flows, adapters, metadata, and the practical difficulty of coordinating many partners and systems.

The participant describes the platform developed by the organisation as a streaming analytics platform that processes real-time data from devices rather than relying on cloud-based analysis. This enables initial data processing close to the data source, which leads to only relevant and processed data being transmitted. This is a way to reduce cloud dependence, improve efficiency, and support real-time decision-making. Another central point of the interview is that digital twins should not be identified as a 3D visualisation. The participant explains that this often happens as many users expect a visual element. Too much focus on the 3D model may distract from the project's actual purpose being digitalisation and optimisation of processes.

NexTArc involves data from many different sources, formats, and owners. Therefore, Participant D emphasises the importance of adapters, metadata, and local data storage. The participant uses temperature as an example, where temperature may seem like simple data, but aspects such as units, location, and sensor type can affect the data. The example shows the importance of metadata and how it can affect decision-making. Another aspect Participant D highlights is the importance of distinguishing between data types. Some data must be near real-time, while others can be collected in advance. A digital twin requires both real-time data pipelines and the usage of prior contextual data. This connects technological architecture directly to usability. Participant D describes how digital twins are a lot more than the visible 3D model, and emphasises the importance of underlying data layers and refinement. Edge AI is a part of the aggregation process, where processing of data at the edge interacts with the central digital twin through APIs.

Regarding collaboration as an organisational factor, Participant D points out that much of the knowledge exchange occurred through informal social interactions during physical meetings. During the interview, physical meetings are discussed as an important factor for collaboration and knowledge exchange. More structured physical meetings are suggested as a good way to improve visibility and increase collaboration. This interview contributes important findings regarding data adaptation, metadata importance, real-time architecture, and the need for mechanisms to increase collaboration and knowledge sharing.

7.5 Participant E

The interview with Participant E contributes with aspects regarding user interfaces and the human-computer interaction side of digital twins. The participant focuses on the visible layer of the system, how data are presented and made meaningful to users. This makes the interview highly relevant for technological and organisational success factors for NexTArc.

During the interview, Use Case 1 is explained as involving a digital twin of an entire neighbourhood. The platform includes large amounts of data, which leads to challenges regarding collecting data and presenting the data in such a way that it is accessible and easily interpreted by users. The digital twin is seen as a tool for simulating resources and supporting decision-making for the physical neighbourhood. This shows how the digital twin is used for planning, resource sharing, and scenario evaluation. Therefore, it is a lot more than a visual representation as it can be used for decision-making. Participant E also argues that the digital twin should not be described as one single product, but as one model consisting of data gathering, information processing, simulations, user interfaces, and systems for decision-making.

When discussing Edge AI, Participant E provides a broad explanation. Edge AI is explained as the possibility to preprocess information on devices before it is integrated into the central system, instead of sending all data to a central server. The possibility to only send processed results reduces processing demands and may reduce energy consumption. Edge AI is therefore described as a decentralised mechanism that can improve efficiency and scalability.

Participant E stresses the importance of face-to-face meetings from an organisation perspective. In larger projects, such as NexTArc, it takes time to establish communication between partners for collaboration and knowledge exchange. The participant describes how previous physical meetings have helped to accelerate communication. Hence, the interview highlights usability, integration, decentralisation, and relationship-building as central success factors for implementation of digital twins and Edge AI in NexTArc.

7.6 Participant F

The interview with Participant F contributes with a perspective from computer engineering, multi-agent systems and dependability. The interview is valuable because it connects digital twin implementation to autonomous systems, data exchange, decision support, and reliability.

Participant F perceives the digital twin as a centralisation point for data. The digital twin has the possibility to send data, retrieve data, and use the collected data to support decision-making. The interview makes clear that the digital twin is not a simple visual or passive model, but a central layer that can help users understand the environment and take action based on that understanding. It is a system with inputs, outputs, decisions, and actions.

During the interview, several key technological components for Edge AI were identified, including sensors, embedded computing boards, and communication systems. The sensors are used to collect information from the environment. The embedded computing boards are smaller units used to process data locally. The communication enables the edge devices to interact with the central system. This provides a clear technological path from sensors to the central system, which can then be used for decision-making and action.

Participant F highlights communication between people as one of the biggest challenges in large projects between many partners. Within NexTArc, it involves people from different backgrounds, including architecture, engineering, computer science, and business. These actors may often have a different understanding of the definition of digital twins and what the project should achieve. For the collaboration to work out, communication is a key aspect. The communication is made through meetings, but the participant explains that the meetings should be better structured or divided by topic so the right people can solve the right problems.

NexTArc is described as a possibility as it gives the opportunity to test new development and research in practice with real data. This is explained as an important organisational and environmental benefit, that complex EU-funded collaborations provide access to realistic settings. This interview shows that successful development and implementation requires robust Edge AI development, reliable communication, and a practical environment in which to test research.

7.7 Participant G

Participant G describes NexTArc from an embedded systems and hardware-oriented perspective. The interview is valuable as it gives a view of the technological foundations of Edge AI and how these relate to digital twin implementation.

Participant G describes the digital twin as a platform that collects sensor data and enables calculations based on the data. The digital twin is therefore described as a collection of sensors and data, although it is described how different actors and partners emphasise different aspects. This illustrates that the digital twin can be understood according to different aspects, such as sensor data, a 3D model, or a whole system.

Technologically, Participant G identifies Edge AI as a key component for the digital twin. Edge devices are used to collect and process data locally before sending it to the central unit. This is important as the data can be sensitive, and when the data are processed locally it reduces exposure and strengthens privacy protection. The participant experiences that one of the main reasons for using Edge AI is privacy, security, and latency. Local processing can be preferable when data should not be exposed or when real-time response is needed. In situations such as heat regulation, low latency can be important.

From an organisational perspective, Participant G describes NexTArc as a learning platform for the organisation, strengthening the organisation through knowledge, and a possibility for communication and collaboration opportunities. Organisational challenges were also explained, including limited experience within the organisation and that the project has had a slow start. The interview contributes to the study by showing how Edge AI development and implementation is shaped by model optimisation, privacy requirements, and organisational learning.

7.8 Participant H

The interview with Participant H provides a research-oriented perspective on Edge AI and digital twin development and implementation. The interview is important as it links the digital twin with optimisation, data-driven AI, and organisation conditions required for implementation.

The digital twin in Use Case 1 is described as both a user-facing interface and a system supported by algorithms that process data. Depending on the goal, the digital twin can be used for optimisation but also decision-making. As an example, Participant H mentions electricity generation and consumption as areas where the collected data can be used for scheduling and resource optimisation. This shows that the digital twin can be used for operational intelligence rather than only visual monitoring. When asked about the most important technological component, Participant H emphasises data. Data are explained as what makes the digital twin unique, and it is critical to being able to create it. This is central as it shows that data availability, access, and quality are critical for the digital twin and its development.

Participant H explains how Edge AI is relevant across several parts of NexTArc. For instance, when processing image data, if the data can be processed locally with AI models, it is a lot easier to send it to the cloud. Local processing can therefore reduce dependence and increase system resilience. The participant also links the use of Edge AI to the ability to operate without relying on external factors. Another factor is security, when locally collected data does not need to be streamed externally, the security issue regarding the data are heavily reduced. During the interview, Participant H also explains technological challenges. The main challenge is that most work in the project is cutting edge. This means that there are few references to follow, which leads to the need to use state-of-the-art analyses. The participant also states that technological success depends on collaboration between partners so each can work within their own area of expertise and support each other.

Organisationally, the participant explains how the organisation benefits from close collaboration with other partners as it provides research, data, and project opportunities. The NexTArc project also creates valuable contacts with partners for future projects. This interview highlights the importance of data, the benefits of Edge AI and opportunities created through partner collaboration.

7.9 Participant I

Participant I contributes with a user-oriented perspective in NexTArc. The participant acts as a link between technical and non-technical actors. The interview is highly relevant as it gives a perspective regarding the organisational factors for implementation success factors, and how it depends on translating technology into practical value.

The participant describes that the digital twin is used to support the physical area. This includes connecting resources, needs, users, and solutions. The digital twin is expressed as a sociotechnical ecosystem for resource visibility and resource allocation. It is used to make the data understandable and useful for users and organisations. Participant I challenges the idea of the digital twin as a simple 3D model with information. It is argued that the 3D view can lead to insufficient user experience if the model presents too much irrelevant information to the user. Therefore, the participant explains that the digital twin should be used as an ecosystem of data and simple ways to access and visualise data. The 3D environment should be different depending on the task the user needs, which creates an important technological success factor. In the interview, digital twins are explained as containing three main layers, databases, data connectors and transformations, and user experience. The database layer consists of organisational systems, building systems, traffic systems, and other external systems. The connector layer retrieves, processes, analyses, and makes data available. The user experience layer provides interfaces for users depending on tasks.

Edge AI is explained as a way to move the processing closer to the sensors, which is especially relevant when the sensors produce large or sensitive data. The participant explains that if all data were processed at the centre of the system, the system becomes large and complex. Camera systems are used as a key example, as they create large amounts of data. If the camera processes data locally and sends conclusions, it reduces latency and issues concerning the security of sensitive data.

Participant I argues that many challenges regarding the project are not purely technological. The main issues are organisational, including gaining access to data, knowing who owns it, and understanding what can be done with it. Many partners have specific technical solutions for the development process, which creates a requirement for collaboration to know how these solutions create value together. However, coordination is challenging due to the large number of partners. This interview contributes to the thesis by showing that digital twin and Edge AI development and implementation requires user-driven design, collaboration, and a constant focus on the value created beyond technological solutions.

7.10 Participant J

The interview with Participant J provides a strategic and organisational perspective on NexTArc and Use Case 1. Participant J describes the digital twin as a tool to identify resources, needs, actors, and flows within an urban district. Data sharing is explained to be central to the digital twin. Without shared data, it becomes difficult to identify unused resources and match resources with new users. The 3D model is explained as an important part of the digital twin. The visualisation of the collected and processed data are explained to enhance the usefulness for users. However, it is also emphasised that different users require different interfaces, due to different interests and needs. Regarding Edge AI, Participant J connects it to prediction, optimisation, and the possibility for future agent-based functionality. It is described how data can be used to predict activity patterns and support better resource planning. Edge AI and ML can therefore be used for broader intelligence of the system, enabling the digital twin to support decision-making, optimisation, and future scenario development.

The main challenges expressed by Participant J are both technological and organisational. One key challenge is to understand each partner's contribution, what sensor data are available, and how different data sources can be connected. This is explained as both organisational and technological challenge, since it requires both technical development and coordination between partners. Organisationally, the participant highlights the complexity of working and collaboration with many partners. The Swedish cluster is smaller and easier to work with, but the project requires coordination, communication, and trust-building. Workshops are explained to be an important success factor, as they create the possibility to support further collaboration and bring together different perspectives. Regarding the importance of collaboration, the participant explains “one plus one must become more than two”, meaning it should create added value beyond what each partner could achieve individually.

Overall, this interview shows that the success of the digital twin depends on the technological components such as data, sensors, and 3D visualisation, but also the ability to create value through collaboration. A key insight is that digitalisation is not only technical, but also highly organisational due to the ways of working and collaboration between partners.

8. Analysis

The following section demonstrates the analysis of the study. Initially, it presents the themes emerging from the thematic analysis. Following, it presents the conceptualisation which led to the conceptual model.

8.1 Themes Emerging from Thematic Analysis

The following section presents the themes identified through the thematic analysis. The themes were developed through selection of keywords from each interview. From there, codes were developed. Based on the codes, six main themes were developed. These are created to answer the research questions and connect the empirical material to the theoretical framework. As the study follows an abductive approach (Dubois & Gadde 2002), the themes are grounded in the interview material but analysed through the Technology-Organisation-Environment (TOE) framework. The TOE framework is considered relevant as it explains how technological innovation is shaped by technological, organisational, and environmental contexts rather than technology alone (Baker, 2011; Tornatzky & Fleischer, 1990).

8.1.1 The Digital Twin as a Sociotechnical System

The first theme that emerged from the thematic analysis shows that the digital twin in NexTArc is not understood as one single technological model, and neither as a visual representation of the Marieberg district. Throughout the interviews, the digital twin is described as a sociotechnical system made up of data sources, sensors, models, simulations, databases, interfaces, visual layers, APIs, and decision-supporting functions. The digital twin should therefore be seen as an infrastructure for connecting the physical urban environment with digital representations, analytical functions and organisational decision-making. This is consistent with literature describing digital twins as systems that support monitoring, analysis, simulation, and decision-making rather than just representation (Fuller, 2020). Other than that, it aligns with research on digital twins that emphasises their role in scenario development before implementation of physical changes (Dembski et al., 2020). Furthermore, this understanding aligns with previous literature about digital twins, where a digital twin is described as a combination between a physical object, a virtual object, and data connections between them (Grieves, 2014). It is also explained that a digital twin requires a high level of data integration rather than only being a static digital model (Kritzinger et al., 2018). This theme captures both the technological complexity and the organisational complexity of creating a shared understanding of the solution.

Several participants challenge the idea of the digital twin as a 3D model. Participant D and Participant I warns that too much attention to the visual 3D layer can distract from the actual value and aim of the digital twin. The 3D model is useful for communication and provides a user-friendly interface, but it is not the core of the system. They emphasised that the value is in how the model connects data, processes, and can be used for decision-making. Participant A emphasises that a digital twin requires a link between data and reality and that this link must be updated and synchronised with real events, which makes a static 3D model not sufficient. Furthermore, Participant E and Participant F describe the digital twin as a broader system that includes data gathering, processing, simulations, interfaces for users, and support for decision-making. This also shows how the digital twin should not be seen as only a technical artefact, but as a bigger system that enables users and organisations to understand and act on information about the physical environment. Participant I presents the digital twin as a sociotechnical ecosystem for resource visibility and resource allocation. This creates a clear link between the technological architecture and the practical value that the system is expected to create.

The interviews also show that the definition of the digital twin is not fully understood across different partners. Participant C described several interpretations of a digital twin, including a digital representation of physical elements, a simulation, and a 3D model covering sensor data. Participant G notes that different actors emphasise different aspects of the digital twin, such as sensor data, visualisation, and the system as a whole. This can be useful as it creates flexibility for innovation. However, it can also create a risk of misalignment, because if different partners have different understandings of the digital twin, the expectations can become unclear. The uncertainty explained is important as the definition has been unclear in previous literature, Kreuzer et al., (2024) show that many digital twin studies lack full data flows and functional feedback loops, which makes it important to clarify what level of integration NexTArc aims to achieve.

In relation to the TOE framework, this theme is mainly related to the technological context, since it concerns the structure, components, and functions of the digital twin. The technological context in TOE describes that the relevant technologies and technical opportunities available to the organisation influence the innovation process (Tornatzky & Fleischer, 1990). The digital twin can be understood as a synthetic technological innovation as it combines existing components into a new integrated system (Baker, 2011; Tornatzky & Fleischer, 1990). It also shows that it also has strong organisational implications. For the technological digital twin to be developed and implemented successfully it is important that the organisations develop a shared view of the definition of a digital twin and its expectations, and what each partner is responsible for. The organisational context of TOE explains that communication, decentralised collaboration, and informal linkages can support innovation processes throughout organisational units (Tornatzky & Fleischer, 1990). Therefore, this theme shows that the technological implementation is inseparable from the organisational interpretation and collaboration between partners. The key success factor related to this theme is that the digital twin should be seen as a multi-layered system rather than a simpler visual model. A key challenge is that different definitions of the digital twin between partners may make the collaboration and integration more difficult.

8.1.2 Data are the Core Enabling Resource for Both Digital Twins and Edge AI

Throughout the interviews it becomes clear that data are a central enabling resource for both the digital twin and Edge AI development, which makes it the second theme. The digital twin is only meaningful when it can access, process, and present data from the physical environment. Data is seen as the foundation that allows the digital twin to become interactive, useful, and connected to reality. This connects directly to the role of IoT devices and sensors, because these are central sources for collecting information from the physical environment (Minerva et al., 2020). Without relevant data, the digital twin risks remaining a prototype rather than an operational tool for simulation, decision-making, and optimisation. This aligns with previous research on digital twins in smart cities, where the value of digital twins depends on the usage of data for simulation, monitoring, and decision-making (Ivanov et al., 2020; White et al., 2021).

Many participants share the view that created the theme, but Participant H expresses this most clearly. Participant H states that data are what makes the digital twin unique and that it is critical for creating it. Participant A focuses on the synchronisation between data and reality, meaning it is critical for the digital twin. Participant B describes the digital twin as a system combining data, databases, computation, and AI. Participant D focuses on how complex data should be used in the project, and emphasises the use of metadata to make it possible to understand, compare, and use the data correctly.

Additionally, it is also shown that data availability is one of the main challenges in the project. Participant B perceives that actual data are missing, which limits the ability to demonstrate functionality. Participant C expresses that the access to relevant data are necessary for the development and implementation of the digital twin. Participant I and Participant J indicate that the difficulty is not only technical, but also organisational. As the project needs to determine who owns the data, who can access it, and how it should be used, it makes it critical to coordinate this between partners. The ability to develop the technological aspect of the project depends on access to relevant data, which depends on agreements and organisational coordination. This links to the TOE framework that argues that technological innovation is affected by both internal organisational conditions and the external environment, including access to resources from other actors (Tornatzky & Fleischer, 1990).

Another important aspect regarding the data is that the digital twin requires different kinds of data. Both Participant B and Participant D express the importance of combining real-time data with static data from databases. As some data must be collected near real-time and some can be collected in advance, it means that the system must be able to handle both dynamic and static data flows. This means that the system must integrate multiple data sources to be able to support understanding of a complex urban district. This finding is supported by related work, which states that digital twin and Edge AI integration has previously been associated with challenges related to system integration, hardware constraints, and standardisation (Rahman et al., 2025). It also relates to the findings made by Kreuzer et al. (2024), describing that many digital twins based on AI rely on historical data and have limited implementation of live data flows and feedback loops. For NexTArc, this makes the combination of real-time data, static data, and feedback mechanisms important.

Related to the TOE framework, this theme is both technological and organisational. In the technological context, data quality, metadata, and integration determine whether the digital twin can be developed and function. This links to the technological context of the TOE framework, as these technologies set the scope and pace of technological change (Collins et al., 1988; Tornatzky & Fleischer, 1990). From an organisational viewpoint, data availability, ownership, and collaboration between partners is needed for the development of the digital twin. The key success factors are therefore access to real and relevant data, clear metadata, and mechanisms for data sharing. The key challenges include missing real data and difficulty of making data usable across organisational boundaries.

8.1.3 Edge AI as an Enabler of Local Data Processing

The third theme concerns the role of Edge AI as a technological enabler in the NexTArc project. Edge AI is primarily expressed as a mechanism that enables processing data close to where the data is generated, instead of sending raw data before processing. This extends from the logic of edge computing, where computation is moved closer to the sensors and devices to reduce the dependence on cloud infrastructure (Satyanarayanan, 2017; Shi et al., 2016). The ability to process data locally is frequently connected to privacy, security, latency, resilience, and efficiency. This relates with related research describing Edge AI with the possibility to inference closer to the data source, which can reduce latency, lower bandwidth usage, improve privacy, and support decision-making (Gupta, 2025; Meuser et al., 2024). Therefore, Edge AI appears to be a critical technological component for creating a scalable and suitable digital twin for the project where large amounts of data are produced and must be processed.

Edge AI gives the possibility to move the computation and processing close to where the data is created. Participant C uses camera footage as an example of when it is especially important. Camera data are typically large and sensitive. If the system processes the data close to the camera and only sends relevant results, the amount of transmitted data reduces. Participant I explains that if all data are processed centrally, the system would become large and complex. This explains why Edge AI can reduce the pressure on the central system and make the processing process more manageable. This can also be connected to the fact that Edge AI is often implemented on devices and embedded systems with limited processing power, memory, and energy availability, which makes local model optimisation important (Marwedel, 2021; Meuser et al., 2024; Singh & Gill, 2023). In regard to the TOE framework, it concerns the technical possibilities and the available technologies that affect the implementation possible (Tornatzky & Fleischer, 1990).

Another valuable aspect of using Edge AI is privacy and security. Participant G expresses that local processing reduces exposure of sensitive data, which strengthens privacy protection. Participant H connects Edge AI to security, as local data does not need to be sent to the central system to the same extent. Participant I also uses camera system as an example, where local processing reduces streaming of sensitive data. This shows that Edge AI is a useful tool for reduced security risks and increased privacy related to data. This relates to the findings from the literature that emphasises privacy-policy enforcement close to where the data are generated (Satyanarayanan, 2017). Furthermore, this also relates to the environmental context of the TOE framework, as privacy and security can be seen as external conditions that can both create opportunities and constraints for innovation (Baker, 2011; Tornatzky & Fleischer, 1990). Ding et al. (2021) emphasise that trustworthy Edge AI depends on transparency, fairness, and robustness. This strengthens the interpretation that Edge AI is a response to wider trust and security requirements.

Reduced latency is also an important aspect of the usage of Edge AI. Participant D explains that processing close to where the data are created allows that only relevant and processed data is sent to the central system. This makes real-time decision-making a lot earlier and reduces cloud dependence. Participant H describes Edge AI as a tool that allows operation with less dependence on external systems. This is particularly useful in this kind of project where delays and central system dependencies can reduce usefulness. Previous research also describes Edge AI as important where low latency and local data processing are critical (Meuser et al., 2024)

This theme primarily belongs to the technological context of the TOE framework. It concerns the technological structure and the capability to process data locally. However, it also has an environmental aspect, as privacy and security are relevant due to a broader external context in which the system operates. The main success factors are the capacity to develop and implement Edge AI for local processing, model optimisation, and architecture related to security and privacy. The main challenges are technical difficulties and the development of the connection between the edge devices and the central digital twin.

8.1.4 Integration as the Main Implementation Challenge

The fourth theme presents that integration is the main implementation challenge in NexTArc. The interviews suggest that the main difficulty for the development of the project is not one main technological problem, but the need to connect many different technologies, data sources, and interfaces. The digital twin requires integration between sensors, edge devices, databases, APIs, models, and visual layers. Meanwhile, the technical integration must take place across multiple partners, since different partners own or develop different parts of the system. This theme relates to the technological context of the TOE framework because it includes both internal and external technologies, and the interaction between these technologies affects which technical changes an organisation can undertake (Tornatzky & Fleischer, 1990).

Participant B discusses a large information gap between the physical hardware layer and the user-oriented layer. This means that the data that is produced by sensors and devices must be processed into information that can be understood and used by users. This challenge is both technological and organisational. The technological aspect is regarding that the system needs interfaces, data structures, and models that have the possibility to transfer the information between layers. The organisational aspect concerns partners and their need to understand how their contributions connect to the wider purpose of the system. Participant D outlines a concrete description of the technological integration challenge. As NexTArc involves data from many sources, formats, and owners, it generates the need for adapters, metadata, and APIs. Participant D also explains that some data must be handled in near real-time while other data can be collected in advance. This shows that integration is also about understanding different temporal requirements and data characteristics. This connects to the need to connect data, local processing, and central digital twin functions, where processed outcomes must be available for simulation, visualisation, and decision-support (Knebel et al., 2023; Minerva et al., 2020). Participant J frames the integration challenge from both a technological and organisational perspective. It is presented as necessary to understand how each partner contributes and what sensor data are available. This shows that integration requires visibility regarding what each partner can contribute with. Participant I explains that many partners have technical solutions, but the challenge lies in understanding how these solutions create value together. This shows that the technological integration challenge is also about aligning solutions into a consistent system. This can be understood as a synthetic innovation, since it is not only about introducing new technology but also about combining existing and emerging technologies into a new system (Baker, 2011; Tornatzky & Fleischer, 1990).

Another part of the integration challenge is regarding reliability. Participant A highlights uptime as a success factor. However, as the digital twin may not fail as a whole system, individual components may fail separately. This is important because it shows that implementation must be understood and assessed at several levels. This makes monitoring and performance evaluation an important technological success factor. Previous research regarding digital twins and Edge AI also discusses reliability as an important outcome of combining technologies (Gupta, 2025; Rahman et al., 2025)

This theme is connected to the technological and organisational context in relation to the TOE framework. The technological context includes APIs, adapters, standardisation, metadata, and reliability. The organisational context includes partner collaboration and shared understanding of the integration. The main success factors are standardised interfaces, metadata, and clarity regarding partner contribution. The main challenges are unclear responsibilities and the difficulty of coordinating integration across partners.

8.1.5 Collaboration between Partners

To conduct a large project with many partners such as NexTArc, collaboration, communication, and shared understanding are important organisational success factors, which makes it the fifth theme from the thematic analysis. During the interviews, it becomes clear that it is the organisational challenges that are the most important. The development and implementation heavily relies on whether partners can coordinate their work and understand each other's contributions. This is particularly important for NexTArc as it is implemented through a large network of partners with different competences, expectations, and responsibilities. This theme aligns with literature describing that digital twins are sociotechnical systems which must be understood and useful for all stakeholders (Barn, 2022; Nochta et al., 2021).

Participant F emphasises communication as one of the biggest challenges in the project. The project includes partners from different backgrounds, such as architecture, engineering, computer science, and business. The partners may not use the same terminology and may not prioritise the same aspects of the system. Some actors may focus on sensors and embedded systems, while others focus on user experience and the visual elements in the project. This is strongly connected to the TOE framework regarding organic structures. Organic structures are characterised by lateral communication, decentralised leadership, and networking between people and units, which are associated with more successful innovation processes (Tornatzky & Fleischer, 1990). Without effective communication, there is a risk that different partners develop separately without a shared understanding of the whole system and the expectations for the project. Communication can be conducted through different approaches. Participant D and Participant E both emphasise the importance of physical meetings. Participant D explains the significance of informal social interactions during physical meetings, and how much knowledge is exchanged during these occasions. Participant E explains that face-to-face meetings accelerate communication. This indicates that physical meetings are meaningful as they help partners understand each other's expertise and can be used to identify dependencies and build relationships. These meetings are therefore not only social events, but practical methods for implementation. Participant J adds the importance of collaboration. The statement that "one plus one must become more than two" captures this importance. Collaboration should create added value, meaning that it should create new value beyond the sum of individual partner contributions.

The interviews state that a challenge in the project is role clarity. Participant B notes that it has been difficult to create and understand the expectations from all partners. Participant J describes the challenge of understanding each partner's contribution and how they should collaborate in the best way possible. Participant I explains that while many partners have specific solutions, the project needs to understand how to create value with these solutions combined. This suggests that partner coordination is also about clarity regarding responsibility and dependencies. Regarding the TOE framework, this can be seen as an organisational implementation issue, where decentralised collaboration may support innovation but also requires effective communication (Baker 2011; Tornatzky & Fleischer, 1990).

In relation to the TOE framework, this theme belongs primarily to the organisational context, as it concerns communication, collaboration, role clarity, project structure, knowledge exchange, and the availability of resources for innovation (Tornatzky & Fleischer, 1990). The main success factors are physical meetings, role clarity, and shared understanding of the project goals. The main challenges are many partners, different disciplinary backgrounds, unclear expectations, and difficulty aligning technical work across organisational boundaries.

8.1.6 NexTArc as a Platform for Learning and Capability-Building

The sixth theme presents that NexTArc is, beyond being a technological project, also is a platform for organisational learning, capability-building and strategic value creation. During the interviews, it becomes clear that the participation in NexTArc gives organisations opportunities to develop technical knowledge, test ideas in practice, and build relationships. This theme broadens the understanding of success in the project, adding that success is also whether participants gain capabilities that can support future projects. This relates to the organisational context in the TOE framework through learning, resources, and knowledge development, and to the environmental context through access to external partners, external knowledge, and the project ecosystem (Tornatzky & Fleischer, 1990).

Participant C broadens the value of NexTArc as it enables product development, technical broadening, and new relationships. This shows that the project contributes to internal organisational development, as it can be used to explore new technical possibilities and position the organisation in relation to future innovation opportunities. Participant G describes the project as a learning platform that has the possibility to strengthen the organisation through knowledge and collaboration opportunities. Participant F discusses the opportunity to test research and development in practice with real data. This is provided through NexTArc, and it is an important environmental benefit. It allows participants to use and develop with actual complex data, devices, users, and systems. The project therefore functions as a link between research, technological development, and implementation. Participant J adds a strategic and collaborative perspective. The project brings together actors with different competences and enables them to combine their contributions. This creates value through the development of technical solutions, but also in the network created. Through this network created, NexTArc can provide future initiatives. This links capability-building to the environmental context, the EU-funded structure creates access to similar organisations that individual organisations may not be able to create alone. Tornatzky & Fleischer (1990) describe the environmental context as including access to resources from others and the organisation’s involvement with the external environment. For NexTArc, the partner ecosystem creates both access to resources and the need for coordination.

Across the interviews, challenges regarding the theme were also discussed. Participant G notes that the project has had a slow start, which can indicate that the learning phase and initiation of collaboration do not always translate into effective implementation, but the participant also notes that the project is still in its starting phase. Large collaborative projects often require time to establish roles, expectations, and ways to communicate. Regarding the same topic, Participant C and Participant J suggest that it is easier to coordinate in the Swedish cluster compared to broader international collaboration. This indicates that strategic benefits in a larger partner network often come with coordination costs. The environmental conditions implies that it also increases complexity. This view is consistent with the TOE framework that the environment can provide both constraints and opportunities for technological innovation (Tornatzky & Fleischer, 1990).

Related to the TOE framework, this theme connects to the organisational and environmental contexts. The organisational context includes learning, internal capability-building, and knowledge development. The environmental context includes access to external partners, EU-funded collaboration, and future project networks. The main success factors are learning, access to partner expertise, real-world testing, and relationship-building between partners. The main challenges are the slow project start, budget and scope limitations, and the difficulty of creating effective implementation through collaboration.

8.2 Conceptualisation

When creating the conceptual model for the thematic analysis, the themes from the interviews are used to conceptualise regarding what is the most important for the development and implementation of digital twins and Edge AI in NexTArc. The TOE framework is used as it provides the theoretical structure for the model. This follows the guide for thematic analysis, where themes developed from the empirical findings are used to develop a conceptual model that represents the most important findings (Christou, 2023; Naeem et al., 2023).

The technological layer consists of the actual technological components that affect the development and implementation of digital twins and Edge AI. The components that emerged from the interviews as the most important are sensors, data pipelines, APIs, metadata, adapters, databases, user interfaces, and visualisations. It explains the most important components for the digital twin and Edge AI solutions to function. Within the technological layer there are a few concepts that are the most important. The first concept is *data infrastructure*, which means the ability to collect, structure, store, share, and interpret data. The processing and use of data are discussed as one of the most important outcomes of the study, as it is needed for the development of the digital twin. The second concept is regarding the processing of the data, which is *edge processing*. Edge processing, meaning local processing close to the sensors and devices, is the main concept regarding Edge AI and is a key element for the development of the digital twin. The third concept is *system integration*.

System integration is concerned with connecting edge devices, central platforms, APIs, data sources, and user interfaces. The last concept is regarding *reliability*, as the system's ability to remain trusted and useful despite modular failures. This concept is concerning that reliability must be assessed at several levels, as the system can fail modularly. These concepts are analysed through the technological context of the TOE framework as they concern the technologies available to the organisations and the technological conditions that set the technological scope and pace (Tornatzky & Fleischer, 1990). This layer connects to literature describing that edge computing is computation close to the sensors and local nodes (Shi et al., 2016), and where Edge AI enables processing of locally generated data before it is sent to the digital twin system (Knebel et al., 2023; Singh & Gill, 2023).

The organisational layer clarifies why the development and implementation cannot be reduced to technology alone. This layer includes coordination, communication, partner roles, user needs, trust-building, and learning. As the organisational layer is explained to be as important as the technological layer, it has also resulted in main concepts. The first concept is *shared understanding*, which is understood as partners needing a common view of what the digital twin is and what it should achieve. The interviews explain that the definition of a digital twin is uncertain, which can make the development of the digital twin difficult. The second concept is regarding *role clarity*, partners must understand what they and others are expected to deliver. To be able to work efficiently, the roles between partners and actors must be clear. The third concept is regarding *knowledge exchange*. During interviews, it is explained that workshops, meetings, and informal interactions help partners align. This concept is also concerning sharing information to achieve role clarity and clarity regarding NexTArc and what is expected. The last concept is regarding *capability-building*, where organisations learn through participating in the project. NexTArc has the possibility for organisations to learn skills that are useful for later projects. These concepts are related to the organisational context within the TOE framework because communication, organisational structure, and slack resources influence innovation processes (Baker, 2011; Tornatzky & Fleischer, 1990).

The environmental layer includes the broader project context, including EU-funded collaboration, multi-partner structure, real-world testing environment, and security concerns. This layer becomes important as NexTArc is a wide-ranging EU-funded project. The first concept in the environmental layer is regarding the *multi-partner ecosystem*, as the development and implementation happens across many organisations. The second concept is about *real-world test setting*. The project provides applied real-world conditions for testing Edge AI and digital twins. As it is a wide-ranging project, it gives the opportunity to test on a large amount of data. The third concept is regarding *privacy and security pressure*. This concept explains the value of using Edge AI as sensitive data can be processed locally. The last concept is *strategic network value*. The project creates future collaboration and innovation opportunities between partners in NexTArc. These concepts correspond to the environmental context of the TOE framework, as industry conditions, external resources, and regulatory conditions can affect technological innovation (Baker, 2011; Tornatzky & Fleischer, 1990).

From the technological, organisational, and environmental layers, a conceptual model is developed. This shows that the cross-organisational development and implementation of digital twins and Edge AI in NexTArc is enabled when technological integration, organisational coordination, and environmental ecosystem conditions are aligned. The conceptual model demonstrates that the implementation process depends on the alignment between these layers. The technological layer must be integrated with the system, but it is shown that this cannot be achieved without comprehensive organisational coordination between partners. At the same time, the environmental layer creates the opportunities and constraints. This is due to the EU-funded project structure providing access to partners, knowledge, and the possibility for real-world testing. Yet, it also increases the coordination complexity. Therefore, the conceptual model shows that successful implementation is affected by the interaction between technical architecture, organisational collaboration, and the broader project environment. This is the main analytical contribution, and it connects to the TOE framework by showing that the technological innovation in NexTArc is shaped by the interaction between technological, organisational, and environmental conditions (Baker, 2011; Tornatzky & Fleischer, 1990). Figure 2 presents the conceptual model of digital twin and Edge AI implementation.

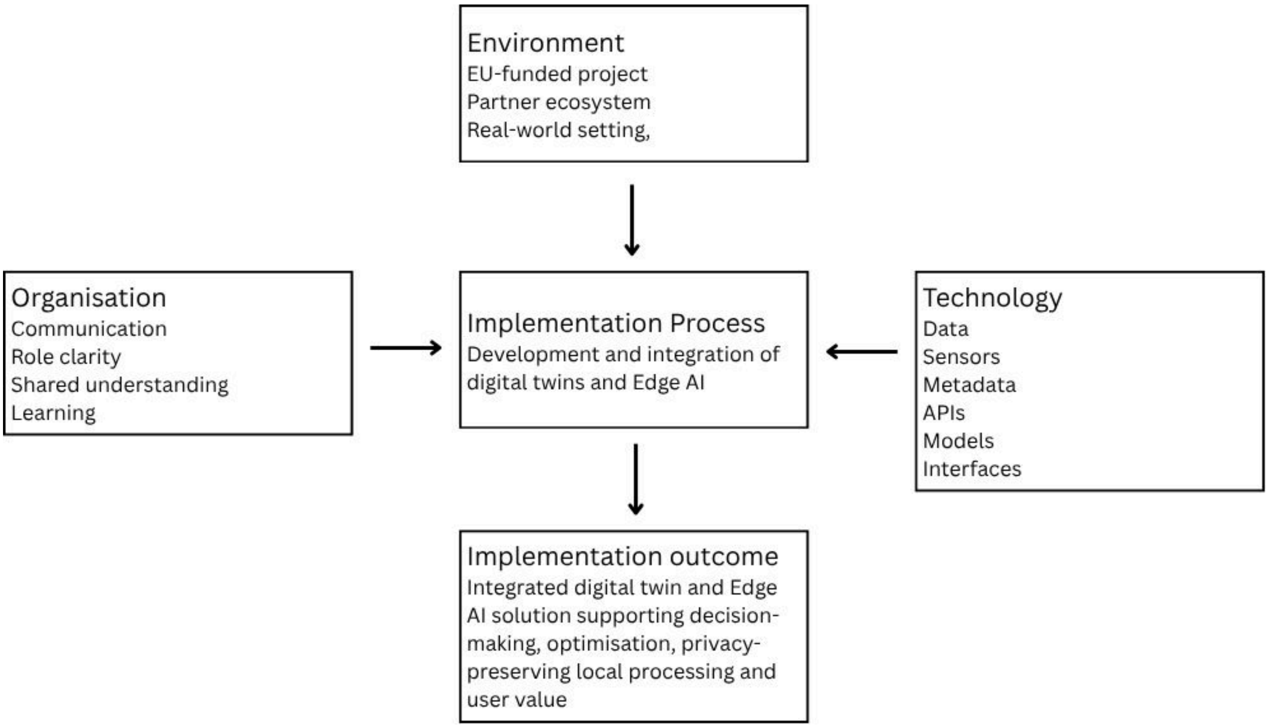

Figure 2: Conceptual model of digital twin and Edge AI implementation in NexTArc

9. Discussion and Conclusion

The purpose of the study was to examine how digital twins and Edge AI are developed and implemented in a complex sociotechnical setting through an in-depth case study of the NexTArc project. Furthermore, the study aims to identify technological and organisational success factors and challenges related to the development and implementation of digital twins and Edge AI. The analysis was based on the Technology-Organisation-Environment (TOE) framework, which has the possibility to broaden the empirical findings related to the interaction between technological, organisational, and environmental findings.

A central finding of the study is that the development and implementation of digital twins and Edge AI are not purely technical. This finding is supported by the sociotechnical perspective on digital twins, where digital twins are not purely technical, but how useful, understandable, and applicable in decision-making also is included in the evaluation (Nochta et al., 2021; Sittig and Singh, 2010). Although the project depends on technological components such as sensors, data pipelines, APIs, metadata, edge devices, and user interfaces, it is shown that the technological components are only useful when they are coordinated across organisational boundaries. This is consistent with the TOE framework, which states that technological innovation is not only dependent on the technological context, but also by the organisational and environmental contexts (Baker, 2011; Tornatzky & Fleischer, 1990). Within NexTArc, the technological solution is developed through collaboration and coordination between multiple partners where different actors contribute with different parts of the system. The success of the implementation depends on the technical architecture, collaboration, role clarity, shared understanding, and access to data.

The first research question examines how technological and organisational factors affect the development and implementation of digital twins and Edge AI within the NexTArc project. The findings from the research show that the technological factors mainly affect the implementation by specifying what is technically possible, what can be developed and integrated, and what value the system can create. To be more specific, the findings show that the development of digital twins are dependent on data flows, simulation, visualisation, and analytics, which also are described as central capabilities in digital twin literature (Dembski et al., 2020; Ivanov et al., 2020; White et al., 2021). The organisational factors affect the implementation by identifying whether the technical components can be coordinated and used by different partners. This shows that the relationship between these two factors influence each other consistently. The digital twin requires a technical infrastructure, but the infrastructure requires organisational alignment to become operational.

The second research question analyses which technological, organisational, and environmental factors enable successful implementation and integration of digital twins and Edge AI across organisational boundaries in the context of NexTArc. The findings indicate that successful implementation is enabled by access to real and relevant data, clear data structures, local processing, standardised interfaces, metadata, shared definitions, role clarity, physical meetings, knowledge exchange, and the ability to build capabilities through collaboration. At the same time, the main challenges are missing or inaccessible data, unclear definitions of digital twins, difficulty of integrating different technical components, unclear partner contributions, and the coordination complexity created by the large project structure. These findings indicate that implementation success depends on more than solving the technological issues. It requires creating a common implementation logic across the project.

9.1 Theoretical Implications of the findings

The findings of this study show that the TOE framework was useful for analysing the development and implementation of digital twins and Edge AI. The framework was used to structure the analysis regarding the technological, organisational, and environmental contexts, which was useful as it connects to the technological complexity and multi-partner collaboration between partners in the NexTArc project. The technological context captured factors such as data infrastructure, sensors, Edge AI, APIs, metadata, models, and reliability. The organisational context captured communication, role clarity, shared understanding, knowledge exchange, and capability-building. The environmental context captured the EU-funded project structure, partner ecosystem, privacy and security, and real-world testing.

Furthermore, the findings also show that the three contexts should not be treated as separate categories in this case, as many of the main findings include multiple categories. The findings including multiple categories is shown in the combination of Edge AI and digital twins, since the development creates possibilities for local processing, while privacy, security, and trustworthiness create environmental requirements (Ding et al., 2021; Meuser et al., 2024). For example, data access depends on technological factors such as data quality, metadata, and interaction, but it is organisational as data ownership and access must be coordinated between partners. Edge AI is technical as it concerns local processing and model development, but it is also environmental as it responds to privacy and security issues. This suggests that the advantage of the TOE framework lies in its ability to show how contexts interact.

The conceptual model, shown in figure 2, shows this interaction between contexts. It shows that successful development and implementation of digital twins and Edge AI in NexTArc depends on alignment between technological, organisational, and environmental contexts. This is the main theoretical contribution of the study. The model shows implementation as an alignment process, and not a linear technical process. The technical architecture must be developed, but it is also connected to the organisational context and environmental constraints and opportunities.

9.2 Practical Implications for NexTArc and Organisations

The findings of the study have several practical implications for NexTArc and for organisations working with digital twins and Edge AI. Initially, the project should precise a definition of the digital twin. This implication is important as previous literature shows that digital twins can be confused with digital models or digital shadows (Kritzinger et al., 2018). The definition should be clear regarding the digital twin not just being a 3D model, but a multi-layered system that connects data, models, simulations, user interfaces, and decision-making. A shared definition can reduce expectation gaps and support coordinated development and collaboration between partners.

Second, the project should prioritise the handling of data and metadata structure. As the data is created through different types of connected devices such as sensors, cameras and other IoT sources (Minerva et al., 2020). Metadata should therefore not be treated as an additional feature, but as an important part of the infrastructure. Data is presented as a central enabling resource. This means that the implementation depends on understanding the data, who owns it, who can access it, and how it can be used. Metadata should be an important part of the usage of data, as it is necessary for making the data interpretable and useful across organisations. Clear metadata can also support integration, reliability, and scalability.

Third, the project should strengthen the mechanisms for integration. The findings suggest that many partners have valuable technical knowledge and solutions, but the project must ensure that these solutions link together into a coherent system. Therefore, the integration should be seen as a central part of the project, not as something that happens automatically after the development of individual components.

Fourth, the project should further include physical meetings, and use them in the best way possible. The findings show that face-to-face interaction supports trust, communication, and informal knowledge exchange. Workshops can also be used to clarify roles, align definitions, and identify integration issues. For a big project like NexTArc where partners work from different organisations, countries, and disciplines, the physical meetings become very important for further development and collaboration.

9.3 Limitations of the Study

When interpreting the findings, the limitations of the study should be considered. First of all, the study is based on a single case study, which means that the findings are context-dependent and should not be understood as statistically generalisable. However, the value of a case study is considered to be the possibility to produce in-depth and context-specific understanding (Benbasat et al., 1987; Gerring, 2007; Thomas, 2011). This leads to the conclusion that the findings may be useful for analytical and naturalistic generalisation, where readers assess whether the case corresponds to their own context (Stake, 1978).

Furthermore, the project is still in an early phase. Several participants have described that the project is in a proof-of-concept phase or still developing. This leads to the findings being connected to the particular phase of the project, rather than evaluating a finished system. Some of the challenges, such as integration, data access, and partner coordination, may change as the project develops further. However, the findings are still valuable because they show what factors are important in the beginning of the project. It also gives the possibility to identify challenges while they are still emerging.

Another limitation of the study is that the study is based on interviews with ten participants. Although the sample was considered sufficient as patterns and themes recurred, the findings may still depend on the perspectives of the selected participants. The participants were chosen to provide variation, as the participants are from different organisations and both project leaders and developers. However, it does not include all possible stakeholders affected by the project, such as users, citizens, or policymakers. Therefore, the study primarily reflects the perspectives of actors involved in development and implementation.

Finally, the analysis was conducted abductively, using the TOE framework while also allowing themes to emerge from the empirical material. The approach for the study made it possible to combine theory and data, but it also leads to that the interpretation depends on the researcher's own analytics. This limitation was reduced as much as possible, by focussing on recurring patterns across interviews and making a clear distinction between the empirical findings and theoretical interpretations. Other than that, the thematic analysis was clearly explained and shown throughout the process.

9.4 Implications for Future Research

When conducting the study, implications for future research were identified. As the study was conducted when the NexTArc project was in its early phase, it would be interesting to examine the development and implementation of digital twins and Edge AI as the project progresses. Future studies could therefore investigate how the identified success factor and challenges progress throughout the project. This is relevant as previous studies shows that many similar studies still have limited implementation of live data flows and feedback loops (Kreuzer et al., 2024) A study of NexTArc in a later stage could therefore examine how the project moves from proof-of-concept towards stronger integration between the physical layer and the digital twin. Another valuable future research would be to examine the perspectives of additional stakeholders. This study examines project leaders and developers within the NexTArc project, but there are other stakeholders that are affected by the project. Future research could therefore investigate urban planners, policymakers, citizens, or other potential users of the digital twin. This would also connect to previous digital city twin literature, where the development of digital twins is central for urban planners and stakeholder engagement (Dembski et al., 2020; White et al., 2021). This would broaden the insights from the project, and it would provide a more in-depth insight into how the digital twin is understood and used by the people expected to benefit from the project. Since the findings from this study emphasises the user interface and decision-support, future research should investigate how different users interpret the value of the digital twin and how they want it to be used.

Another aspect of this study is that it is a case study of a single case. Future research could investigate other projects regarding digital twins and Edge AI, with the aim to compare the NexTArc project with other similar projects. This type of study would be able to examine which findings are specific to NexTArc and which are more general for similar projects. This would strengthen the generalisability of the findings and provide knowledge regarding the technological, organisational, and environmental factors in these settings.

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Appendix

Appendix A: Interview Script

Introduction
My name is Hugo and I am currently pursuing a Master's thesis. The purpose of the thesis is to conduct a case study of NexTArc to examine how digital twins and Edge AI solutions are developed and implemented. The study also aims to identify the key technological, organisational, and environmental success factors, and challenges that arise.

The study focuses on Use Case 1, so all questions are related to UC1.

Introductory questions
- Tell me about yourself and your role in the organisation.
- What is your role in the NexTArc project?
- How long have you been involved in the project?

Technical questions
- How would you describe the role of digital twins within the NexTArc project?
- In what ways do you work with digital twins?
- What technical components are required to build and operate the digital twin in this project?
- How would you describe the role of Edge AI within the NexTArc project?
- In what ways do you work with Edge AI?
- What technical components are required to implement Edge AI in this project?
- How are Edge AI solutions integrated with digital twins?
- Why was Edge AI chosen as part of the solution in the project?
- What technical challenges have you encountered during the implementation?
- What technical factors have been particularly important for the success of the implementation?

Organisational questions
- Describe your organisation and its role in the project.
- How does participation in NexTArc affect your organisation?
- What organisational challenges have you encountered during the implementation?
- What organisational factors have helped enable the implementation?

Environmental questions
- How does the collaboration work between the different organisations involved in the project?
- What challenges have you encountered when coordinating work between multiple partners?
- How do requirements from the EU affect the project?

- Are there regulatory, legal, or policy-related factors that affect the implementation of Edge AI?
- What external factors have been most important for the success of the project?

Closing questions

- What lessons from this project could be useful for future Edge AI implementation?
- Is there anything important about Edge AI or digital twins that we have not discussed?