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Integrating generative AI into the analytics workflow

Streamlining and transforming workflows in a global organisation

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Abstract

As data becomes an increasingly central recours in modern organisations, expectations around how it is collected, processed and analysed continue to grow. In this transformation, AI and particularly generative AI has begun to play a more prominent role. While generative AI shows strong potential to streamline analytics workflows, its rapid development raises questions around practical application, limitations, and the organisational conditions needed to unlock its full value.

This thesis explores the integration of generative AI into analytics workflows within a large globally operating telecommunication company. Through a qualitative research approach and semi-structured interviews, the study investigates where and how generative AI can be implemented to enhance efficiency and decision-making. The analysis applies the technology-organisation-environment (TOE) framework to explore the empirical data from different perspectives and capture the interplay between technological, organisational and external factors. Findings show that generative AI holds significant potential to streamline repetitive tasks such as coding, data structuring and reporting. However, realising these benefits requires clear prompts, high- quality data and users who understand both capabilities and limitations of the tools. Human-AI collaboration emerges as a success factor, highlighting the need for both technical and interpretive skills among users. The study concludes that to fully realise the potential of generative AI, organisations must invest in data governance, foster a culture of innovation, and develop practices that support collaborative interaction between humans and AI.

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Populärvetenskaplig sammanfattning

I takt med att data blir en allt mer central resurs i moderna organisationer växer också kraven på hur den samlas in, hanteras och analyseras. I detta skifte har artificiell intelligens (AI), och särskilt generativ AI, börjat spela en mer framträdande roll. Till skillnad från traditionell AI som generellt tränas för att lösa avgränsade uppgifter, kännetecknas generativ AI av sin förmåga att skapa nytt innehåll, exempelvis kod, text och visualiseringar, utifrån en given kontext. Just denna förmåga gör tekniken särskilt lovande inom analytiskt arbete, där uppgifter som tidigare krävde manuellt arbete och expertis nu kan automatiseras och förenklas. Verktyg som bygger på generativ AI har potential att effektivisera arbetsflöden, minska trösklar till avancerad analys och på sikt bredda tillgången till beslut baserat på data. Samtidigt väcker den snabba utvecklingen frågor om hur tekniken faktiskt används i praktiken, vilka möjligheter den erbjuder, vilka begränsningar som uppstår och vilka organisatoriska faktorer som avgör om dess potential kan realiseras.

Trots den tekniska potentialen är implementeringen av generativ AI i praktiken sällan friktionsfri. Stora organisationer kännetecknas ofta av komplexa strukturer, fragmenterade datasystem och inarbetat arbetssätt som inte alltid är anpassade för ny teknologi. Samtidigt saknas det ofta gemensamma definitioner och tydliga riktlinjer för hur AI-tekniker bör användas vilket skapar ett glapp mellan teknikens möjligheter och dess faktiska tillämpning. Det analytiska arbetsflödet är ett centralt område där generativ AI kan skapa värde. Men för att förstå när, hur och varför tekniken verkligen bidrar krävs en djupare förståelse för de organisatoriska, tekniska och externa faktorer som påverkar dess användning.

Syftet med detta examensarbete är därför att undersöka hur generativ AI kan effektivisera beslutsprocesser inom en stor, global organisation. Genom en kvalitativ studie, med intervjuer som huvudsaklig metod, undersöks hur tekniken används, vilka vinster och begränsningar som upplevs, samt vilka organisatoriska förutsättningar som påverkar dess praktiska tillämpning.

Resultaten visar att generativ AI framför allt kan användas för att effektivisera skrivning av kod, strukturera data och automatisera rapportering. Detta skapar tidsvinster och möjliggör för analytiker att fokusera mer på insiktsarbete än på repetitiva uppgifter. Samtidigt framkommer ett antal begränsningar. Effektiv användning av generativ AI förutsätter tydliga instruktioner, korrekt datastruktur och förståelse för modellens möjligheter och begränsningar. Vissa användare utvecklar snabbt förmågan att samarbeta med AI, medan andra upplever en osäkerhet kring hur tekniken ska användas. Den kompetens som krävs vid användandet av generativ AI handlar inte enbart om tekniskt kunnande, utan om att kunna formulera rätt frågor och kritiskt värdera svaren.

Utöver tekniska och individuella faktorer identifieras flera organisatoriska hinder. Brist på gemensamma datadefinitioner, fragmenterade system, låg tillgång till data och en försiktig innovationskultur minskar möjligheterna att dra nytta av AI-verktyg. Även externa faktorer som regulatoriska krav och säkerhetsfrågor påverkar möjligheten till experiment och bred tillämpning. För att kunna utnyttja teknikens fulla potential krävs bland annat en förståelse för dess tillämpningsområden och en organisationskultur som främjar innovation.

Analysen genomförs utifrån TOE-ramverket (technology, organisation, environment), vilket möjliggör en systematisk förståelse för hur tekniska, organisatoriska och externa faktorer tillsammans påverkar teknikens genomslag. Sammanfattningsvis visar studien att generativ AI har stor potential att effektivisera och förbättra analysarbetet samt stödja datadrivet beslutsfattande, men att denna potential endast kan realiseras om tekniken används i rätt sammanhang, med rätt kompetens och inom en struktur som möjliggör samverkan över organisatoriska gränser.

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1. Introduction

In an increasingly digitised world, data analysis has emerged as a central part of business development and operational decisions. For large organisations with global distribution there is a daily handling of a great amount of data, from customer interactions and network performance to financial forecasting and resource planning. These organisations usually operate in complex ecosystems and to maintain competitiveness and optimise operational processes, effective data management and analysis are essential (Davenport, 2006).

Despite extensive investments in data-driven systems and analysis tools, handling large amounts of data remains a challenge. Traditional workflows are usually dependent on manual work, where data must be extracted, cleaned, transformed and analysed through a series of time-consuming processes before it is useful for comprehensive purposes. This process can be both time-consuming and labour-consuming, which limits the ability to act quickly on changes in the market or in operational activities. In addition, the management of different data sources, from structured to unstructured data, represents a technical challenge that requires both advanced tools and specialist skills (Kelleher, J.D & Tierney, B., 2018).

For a large technology and telecommunication company with a global delivery of infrastructure and other services, these challenges become tangible (Ericsson, (n.d.); (Kelleher, J.D & Tierney, B., 2018). It requires constant maintenance and development to be able to offer improved network performance and ensure safe predictive analyses. Addressing these needs in a scalable and automated way is critical to being able to meet the increasing demand for fast and stable communication, while optimising cost and resources (Folorunsho, S.O. et al., 2024).

Generative artificial intelligence (AI) has, in recent years, emerged as a transformative technology across various industries, offering the potential to automate complex workflows. By automating certain parts of the workflow, generative AI could be used to streamline data collection and preprocessing by removing the need for a human to manually clean, structure and categorise large amounts of data. Furthermore, it can be used to generate SQL-code, which in turn enables more flexible and faster analyses where there is no longer a need to manually write long and advanced code. Through analyses of historical data, patterns can be identified and thus offer improved decision support and predictive models. In order to broaden the availability of the analysis tools to the masses without technical background, generative AI can also enable interaction with data through natural language (Dwivedi, Y.K. et al., 2023).

Despite the possibilities that generative AI brings, there are several challenges that need to be addressed before it can be implemented at scale. Robust data governance and security frameworks are required, especially in organisations dealing with sensitive information. Transparency and explainability of the systems is desired to ensure trustworthy results. The implementation of generative AI ultimately requires an adaptation of existing work processes and IT infrastructure, where the collaboration between human analysts and AI becomes a central key for success (Dwivedi, Y.K. et al., 2023).

This thesis aims to investigate how generative AI can be integrated into analytical workflows in an organisation with extensive data-driven decisions and global operations. By identifying opportunities and challenges with AI-driven analytics, the results can help improve efficiency and availability in data-driven decision-making. Not only in this specific organisation, but also in other industries where data management and analytics are critical parts of the business.

1.1 Research background

This study is conducted on behalf of Ericsson AB, a global leading company in telecommunications and network technology. Founded in 1876, the company was early in digital transformation and has played a decisive role in the development of innovative communication solutions worldwide. With operations in over 180 countries, more than 100 000 employees globally, and a long history of technological development, the company has established itself as one of the most influential players in the industry. By driving the development of advanced technologies, such as 5G and IoT, the company aims to enable better connectivity and digital services that shape the society of the future (Ericsson, n.d.).

Ericsson, as a globally operating and technologically advanced organisation, has an extensive and multi-layered structure for governance and decision-making. Organisationally, Ericsson is divided into group functions including finance, legal affairs and compliance, technology, people, marketing and corporate relations, support and operations. This together with five business areas and four geographical market areas. This structure enables both strategic coordination at a global level and local adaptation to market-specific needs (Ericsson, 2024).

The decision-making structure within Ericsson is based on a clearly defined governance model regulated by the Swedish Companies act and supplemented by internal guidelines. The board of directors is ultimately responsible for Ericsson's organisation, strategy and operations and works through four committees. The operational management consists of the CEO and the executive team, including functional managers as well as heads of Ericsson's five business areas and four market areas. Ericsson's corporate office plays a central role in defining the company's overall strategy, governance and policy, and in ensuring a coherent framework for decision-making and risk management. This structure reflects the company's size, global operations and technological complexity (Ericsson, 2024).

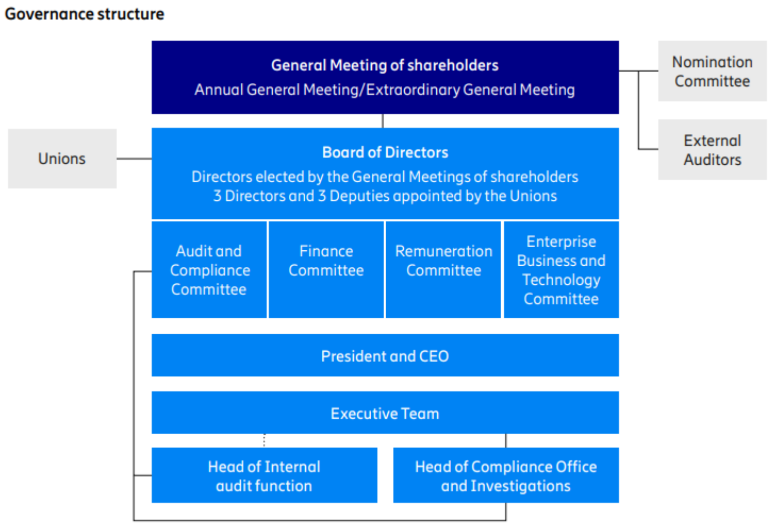

Figure 1: Governance structure at Ericsson (Ericsson, 2024)

As the organisation has become increasingly data-driven, the need for structured data management and internal governance of information has increased. To address this, Ericsson has established a dedicated data enablement office, which is responsible for data governance, data quality, security and architecture, which was introduced in an interview with Sonia Boije performed by McKinsey (McKinsey & Company, 2023). The company has implemented a federated data model, meaning that data responsibility is distributed across different parts of the organisation which in practice means that business stakeholders in different parts of the business own and are responsible for the data areas that are relevant to their function. By involving these actors from the beginning, both local ownership and a more effective data governance structure aims to be created.

Ericsson has also identified the need to change its data culture, from a tradition of restricted access to a more open, accessible and collaborative environment. This aims to make data and insights more attainable throughout the organisation, strengthening data-driven decision-making capabilities at all levels (McKinsey & Company, 2023).

1.2 Purpose and research questions

This study explores the role of generative AI in analytics workflows, assessing where and how it can be implemented to enhance efficiency and decision-making within a large, globally operating company. The research will examine key processes to identify both opportunities and challenges associated with the integration of generative AI.

1. What are the major challenges and enablers associated with an organisation's adoption of generative AI and its integration into the analytics workflow?

2. In what ways can generative AI enhance efficiency within the analytics workflow, and how does it contribute to more effective decision-making?

2. Introduction to organisational decision-making and artificial intelligence

2.1 The nature of organisational decision-making

In today's rapidly changing business landscape, effective decision-making is a critical competitive factor. The ability for organisations to make informed decisions in a timely manner affects not only their internal efficiency, but also their position in the market (Edwards et al., 2000). As organisations grow in complexity, the amount of information that decision-makers are expected to consider also increases, making supporting technologies increasingly important.

Decision-making is a central component of organisational success, it takes place at all levels of management and involves employees throughout the organisation (Edwards et al. 2000; Kozioł-Nadolna et al., 2021). A decision-making process can be defined as the structure and methods used to reach a decision. While the process may vary depending on the model, its overall structure remains consistent. It typically consists of multiple steps including; problem identification, information gathering, evaluation of alternatives and implementation of the decision (Kozioł-Nadolna et al., 2021). Decision-making is often an iterative process that involves issue-framing and intelligence-gathering. According to Russo et al. (2024), its primary objective is to enable individuals or groups to reach well-informed conclusions about future actions based on specific goals.

Decisions made in organisations can be categorised into different types depending on their nature and scope. Kozioł-Nadolna et al. (2021) distinguishes between programmed and non-programmed decisions, where programmed decisions are described as repetitive and guided by routines or established procedures while non-programmed decisions are unique, more complex and often arise in unpredictable situations. Another classification divides decisions into strategic, tactical and operational levels. Strategic decisions are long-term decisions often with high impact that define the organisation's future direction. This includes for instance setting goals and scaling strategies. Tactical decisions focus on implementing plans and actions to achieve the strategic goals. Lastly, operational decisions are routine-based decisions that are made everyday (Kozioł-Nadolna et al., 2021). Decision-making is affected by both internal and external factors, and depending on the situation may be driven by rational choices, intuition or even emotions (Kozioł-Nadolna et al., 2021).

Figure 2: The hierarchy of decisions (Future CIO club, n.d.)

In the context of this study, the focus lies on a large and complex organisation operating in the technology and telecommunications sector. The organisation is characterised by its global presence, data-driven work processes and cross-functional structure, where decision-making takes place at multiple levels within different business areas (Ericsson, 2024). Given the nature of the organisation, all types of decisions are of interest and are touched upon in the study. For operational decisions, there is a clear approach to streamline processes with the use of generative AI. In the long term, however, strategic decisions are considered of primary interest to investigate since these are long-term and cross-functional decisions that affect the future direction of the organisation.

2.2 Exploring the landscape of artificial intelligence

2.2.1 The foundations and historical developement of artificial intelligence

Artificial intelligence is a widely recognised and frequently used term in today's society, but despite its popularity, there is no general definition of AI (Sheikh et al., 2023). John McCarthy was the first to introduce the term in 1956 which marked the beginning of AI as a formal academic discipline (Haenlein & Kaplan, 2019). Since then, numerous definitions have been proposed, each reflecting different perspectives on what constitutes intelligence and how it should be measured in machines. The lack of consensus is partly due to the complexity of intelligence itself, something we still don't fully understand. One recurring theme in AI research is the so-called "AI effect," where technologies that become widely adopted or thoroughly understood are no longer seen as genuine AI. As Haenlein and Kaplan (2019) explain, the perceived magic of AI often disappears when the underlying technology is demystified.

Given these complexities, Sheikh et al. (2023) adopts an open definition of AI: "systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals". This approach is broad enough to include current and future technologies, while still distinguishing AI from traditional software.

The evolution of AI has occurred in waves, where different approaches to AI have been more or less dominant. One approach is symbolic AI or rule-based systems, often referred to as expert systems. These systems use predefined "if-then" rules to define how the system should behave (Sheikh et al., 2023). In recent years, the focus has shifted to artificial neural networks and machine learning, particularly deep learning (Haenlein & Kaplan, 2019). This approach enables systems to learn patterns and improve performance from data rather than following fixed rules (Sheikh et al., 2023). Technologies such as facial recognition, voice assistants and autonomous vehicles are all based on these self-learning systems (Wamba-Taguimdje et al., 2020).

2.2.2 How machines learn through machine learning and deep learning

Machine learning is a subset within the broader field of AI that focuses on enabling systems to learn from data and improve their performance over time without being explicitly programmed for every task (Alzubi et al., 2018). There are several types of machine learning but two of the most common approaches are supervised and unsupervised machine learning. In supervised machine learning the dataset is labeled, which means each input comes with a corresponding, known output. The goal is for the system to learn the relationship between inputs and outputs so that it can accurately predict the output for new, unseen data (Lindholm et al., 2022).

Unsupervised learning deals with data that has no predefined labels. The objective here is not to predict a specific outcome, but rather to explore the structure of the data itself. The model tries to identify patterns, groupings, or underlying features that might not be immediately obvious (Alzubi et al., 2018). Two common techniques in unsupervised learning are clustering, which involves grouping similar data points together, and dimensionality reduction, which simplifies data while retaining its essential features (IBM, n.d.a).

Deep learning is in turn an advanced branch of machine learning that uses artificial neural networks inspired by the structure and function of the human brain. These networks are composed of many layers, enabling them to learn complex patterns from large amounts of data. Deep learning has been particularly successful in fields such as image recognition, natural language processing, speech synthesis and autonomous systems. This success was made possible by advances in computing power and access to large datasets. Deep learning has laid the foundation for the emergence of today's generative AI (IBM, n.d.b).

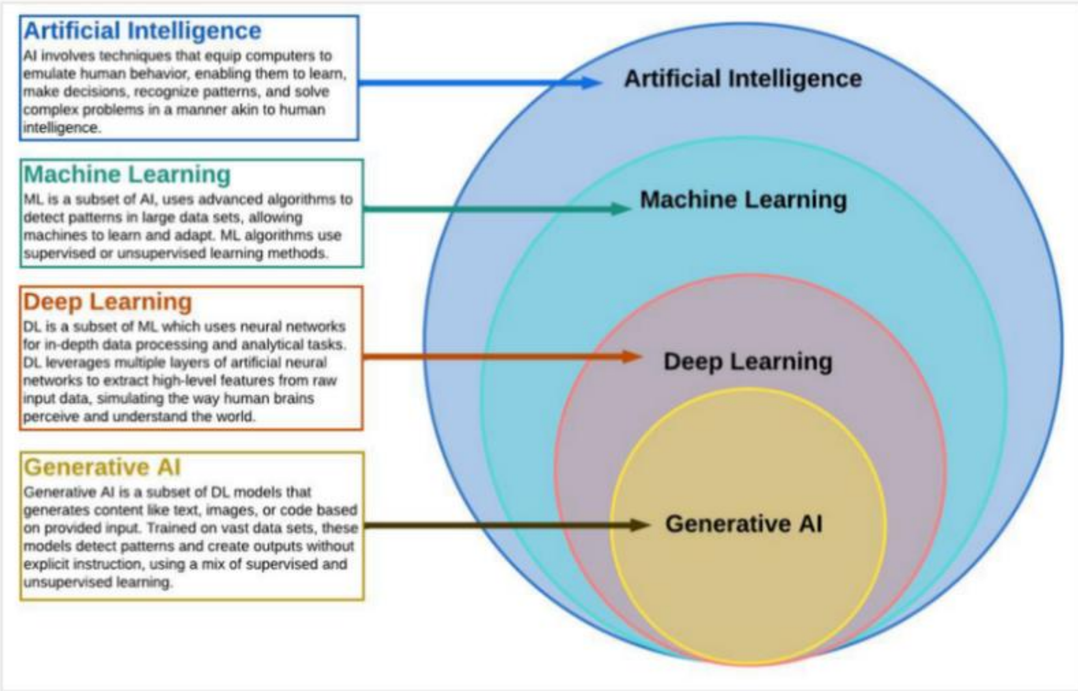

Figure 3: Figure illustrating the relation between AI, machine learning, deep learning, and generative AI (Popova Zhuhadar, n.d.)

2.2.3 Generative AI and its role in innovation and analytics

The transformative technology generative AI has rapidly emerged with the ability to generate data that has a close resemblance to real-world data (Bandi et al., 2023). Muller et al. (2022) is defining generative AI as "an AI system that uses existing media to create new, plausible media". In comparison to traditional AI systems, focusing on analysis and prediction, generative AI can give us images, text, music and other complex designs which opens new possibilities across various domains, including healthcare, entertainment and business analytics (Bandi et al., 2023). However, it may not only be used for artistic purposes but to assist humans as intelligent question-answering systems (Fuerriegel et al., 2023). With the use of generative AI, technology is moving past automation and is instead fostering innovative decision-making, adaptive responses and improved data quality. The use of generative AI may however come with a prize and new challenges such as data governance, technical complexity, explainability and user trust needs to be taken into consideration (Bandi et al., 2023).

3. Theoretical framework

To understand how generative AI can impact analytics workflows and organisational decision-making, this study draws on a range of theoretical perspectives. By combining insights on AI-supported decision-making, automation, human-AI collaboration, and technology adoption, the theoretical framework provides a foundation for analysing both opportunities and barriers related to generative AI. Together, these perspectives offer a multidimensional lens through which to interpret the findings and understand the broader organisational implications of this emerging technology.

3.1 Leveraging generative AI for organisational decision-making and analytics

3.1.1 Artificial intelligence as support in decision-making

AI in decision-making has developed significantly in recent years, primarily driven by advances in machine learning, big data and deep learning. Unlike earlier expert systems which depended on manually coded rules, modern AI leverages probabilistic reasoning, neural networks and reinforcement learning to improve decision accuracy (Duan et al., 2019). The integration of AI in decision-making processes is seen as highly beneficial due to its ability to enhance speed, cost-efficiency and accuracy (Shrestha et al., 2019).

This development has been made possible by big data technologies, allowing AI to learn from vast, unstructured datasets. By leveraging probabilistic reasoning, neural networks and reinforcement learning, AI can now improve decision accuracy beyond what rule-based systems were capable of (Jarrahi, 2018; Cao et al., 2021).

A key aspect in determining how AI should be applied is the nature of the decision itself, particularly its level of uncertainty and structure. There is some level of uncertainty related to all types of decisions made within a company and according to Brink et al. (2023) it is typically the highest for strategic decisions. For tactical and operational decisions the degree of uncertainty diminishes sharply. On one hand, it is argued that AI is most suited when handling decisions with low uncertainty, but it is also assumed to be a greater potential value for AI when making decisions with a high degree of uncertainty (Brink et al., 2023). Magliocca et al. (2024) argue that generative AI is particularly well-suited for operational decision-making, as such decisions are typically rule-based, data-driven, and repetitive. These are characteristics that align well with the strengths of AI in terms of efficiency and scalability. Tactical decisions often demand contextual understanding and nuanced interpretation, which means that human involvement remains essential in this domain (Brink et al., 2023; Magliocca et al., 2024). Strategic decisions are the most dependent on human judgment, as they involve navigating high uncertainty and assessing long-term implications. While AI can offer valuable input in strategic contexts, it is not positioned to function as the primary decision-maker (Magliocca et al., 2024).

This reasoning applies not only to traditional AI systems but also to generative AI. Hyunh (2024) says generative AI can act as a powerful cognitive assistant in decision-making but as for traditional AI is dependent on human verification. Generative AI holds great promise, especially in enhancing human cognition in decision processes, its effectiveness is deeply tied to how it is perceived and governed within organisations (Hyunh, 2024).

3.1.2 Enhancing analytics efficiency and flexibility through generative AI automation

Making informed decisions in complex organisations requires an efficient and reliable analytics process. The analytics workflow serves as a core component of decision-making, from collecting and processing data to interpreting and presenting insights (Drosos et al., 2024).

Drosos et al. (2024) says that the use of generative AI in data analysis has increased significantly and he believes that it has the potential to change the entire analysis workflow. Research conducted by Drosos et al. (2024) shows that generative AI can assist in all phases of the analysis process, from data collection to final visualisation and reporting. By leveraging large language models and advanced machine learning algorithms, AI can generate, interpret and structure data in ways that can streamline and automate workflows.

In data collection generative AI can contribute by identifying relevant sources of information, generating initial research questions and aggregating data from various sources. Drosos et al. (2024) mentions, as an example, the use of AI systems to automatically extract information from web pages, scientific articles and databases, reducing the initial workload for analysts. One of the main benefits of AI in data collection is the ability to quickly identify patterns and contexts in large amounts of unstructured information. However, there are challenges linked to data quality and source criticism, as AI systems can include irrelevant or unreliable sources if not properly configured. The generated research questions may also lack depth or relevance if the AI does not have sufficient contextual understanding (Drosos et al., 2024).

During data preprocessing, AI has the potential to automate tasks such as data cleaning, handling of missing values, normalisation and transformation of data values. According to Drosos et al. (2024), this could be especially valuable in complex datasets where manual methods are time consuming. This involves risks such as the AI system making incorrect assumptions about the underlying data structure, as well as the potential introduction of bias, which may in turn compromise the validity of future analyses. Therefore, Drosos et al. (2024) believes that human review and validation of AI generated preprocessing is required.

As for the analysis itself, generative AI has proven to be able to generate code, perform statistical calculations and creative predictive models. AI models are able to write python or SQL code for data analysis and interpret results based on descriptive statistics. This reduces the need for manual coding and can help analysts quickly generate insights (Drosos et al., 2024). In visualisation and reporting, generative AI can be used to automatically create charts, dashboards and text-based summaries of analysis results. It is viewed as possible for AI to suggest what types of charts best represent a particular data set or generate written summaries that explain trends and patterns in the data (Drosos et al., 2024).

Drosos et al. (2024) emphasises several risks with generative AI in analysis workflows, such as lack of context understanding. The risk is that AI lacks domain-specific expertise and may therefore generate results that are technically correct but analytically irrelevant, as well as that users have to ask questions in a very precise way to get useful answers, which requires some understanding of the data and the model. There is also the risk of AI hallucinations, that generative AI produces answers that sound convincing but are factually incorrect or unsupported by data. This highlights the need to combine AI with human expertise to ensure accurate and reliable analyses (Drosos et al., 2024).

3.2 Human-AI collaboration in data analytics

3.2.1 Redefining human-AI interaction

As AI continues to evolve, the way humans interact with AI systems is also changing. Historically, the interaction has followed a delegation model, where humans assign tasks and the AI executes them. However, with generative AI, we are reaching a further point of refinement. The interaction is now more collaborative and iterative, humans prompt the AI to perform a task, receive a response, and adjust their input based on that, leading to a dynamic exchange (Feuerriegel et al., 2024).

This transformation has led scholars to explore new ways of conceptualising the interaction between humans and AI. One key discussion is whether values can truly be embedded into AI systems. Johnson and Verdicchio (2024) challenge this notion and argue that AI and values cannot be combined in an additive way. Instead, they propose a sociotechnical approach that sees AI not only as computational code and algorithms, but as part of a broader system influenced by social structures, human decision-making and organisational dynamics.

According to their view there are two ways of understanding AI, as computational artifacts and as sociotechnical systems. The latter acknowledges that AI outcomes emerge through the interaction between code and the human and societal context in which it operates. Bias, for example, cannot be explained solely by examining code, it must also be understood in relation to economic structures and institutional choices. Thus, the values and functions attributed to AI are not fixed, but co-created in practice.

3.2.2 Designing usable and accessible AI systems, the contribution of Human-Computer-Interaction

As AI systems become more deeply integrated into analytics workflows, usability and human-centered design are becoming increasingly important. Human-Computer-Interaction (HCI) theory addresses how people interact with technology and provides guiding principles to make that interaction more efficient, accessible and intuitive (Norman, 2013; Schneiderman, 2020).

In traditional analytics workflows, a high level of technical knowledge is often required, which limits accessibility for non-experts. Generative AI can reduce these barriers by enabling natural language interaction and simplifying queries, making analytics tools easier to use across a wider range of roles in the organisation (Shneiderman, 2020). This development opens new possibilities for more inclusive, data-driven decision-making.

HCI is grounded in the belief that interaction between human and machine should be seamless and adaptable to different user contexts, whether in terms of expertise, expectations, or needs (Norman, 2013). In relation to generative AI, this means designing systems that are not only powerful but also intuitive and aligned with how people actually think and work. According to Binns (2018), the increasing autonomy of AI systems calls for even stronger emphasis on human-centered design, including transparency, adaptability and a clear sense of user control.

These insights highlight the importance of involving users in the design and evaluation of AI tools, not only to improve functionality, but also to build trust, comprehension and ultimately, more informed use (Norman, 2013).

3.3 The adoption of generative AI

Even though AI offers great potential to improve efficiency, speed and analytical capabilities in decision-making, its integration into the everyday life of organisations is far from uncomplicated. As generative AI becomes an increasingly active part of analytics workflows, a new type of challenges emerge that are not solely technical in its nature (Shresta et al., 2019). Generative AI no longer only functions as a passive analytical tool, but has the potential to actively participate in decision-making processes by generating suggestions, insights or even finished drafts. This is changing both how decisions are made and who makes them, raising questions about accountability, transparency and trust (Jarrahi, 2018; Huynh, 2024). It challenges organisational structures and requires new forms of interaction between human expertise and algorithmic decision support (Wilson & Daugherty, 2018).

The challenges are therefore not only technical, but organisational, cognitive and ethical. At an organisational level, new structures for data governance, division of responsibilities and workflows are required (Wamba-Taguimdje et al., 2020). Cognitively the users are faced with new demands to be able to interpret AI generated outputs, understand its limitations and manage tools that are based on prompt-based interaction (Huynh, 2024). Ethically, questions of bias, opacity and responsibility are raised, especially when AI models function as a black box and their suggestions risk being taken for truth without critical review (Cao et al., 2021).

To analyse challenges and enablers, this study applies the Technology- Organisation-Environment (TOE) framework, which provides a structured lens for understanding how organisations adapt and assimilate technological innovations (Abu-Khadra &

Ziadat, 2012). The framework was introduced in 1990 by Tornatzky and Fleischer who identified three contextual dimensions that influence the implementation of new technology, which are the technological context, the organisational context and the environmental context. TOE has been widely used in empirical research and has proven applicable to various types of technological innovations. Given its comprehensive structure and adaptability, the TOE framework is particularly well-suited for capturing the multidimensional nature of generative AI adoption, where technological capabilities, organisational readiness, and external pressures intersect.

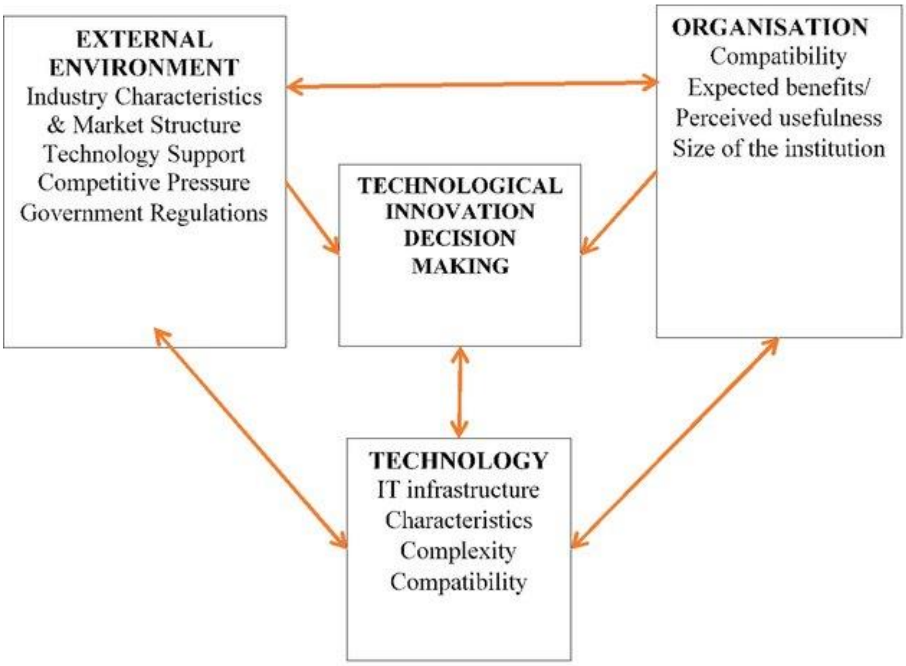

Figure 4: The TOE framework (Tornatzky & Fleischer, 1990)

3.4 Challenges and enablers of AI adoption in a technological context

The technological context in the TOE framework includes internal and external technologies that are relevant to the organisation, meaning both existing technologies and emerging innovations like generative AI. Key factors in this context include the functionality, complexity and usability of the technology as well as how well it integrates with current systems and infrastructure.

3.4.1 Hallucination and output reliability

Despite the great potential of generative AI to streamline workflows and support decision-making, several technical limitations remain that need to be addressed. One of the most noted risks is that the models generate incorrect or misleading answers. As Feuerriegel et al. (2024) points out, generative AI systems are designed to always generate an answer, which can lead to the most probable answer being given and not necessarily the most correct one. This probability-based logic means that the model risks hallucinating, that is, creating credible but fabricated content. To address this, Tancredi (2024) identifies strategies that organisations can use to increase the reliability of AI-generated content. One important method is to introduce human-in-the-loop, where humans review and quality assert the output before it is used in decision-making processes. To increase accuracy in specific use cases, it is also recommended for the model to be fine-tuned with high-quality, domain-specific data. This, Tancredi (2024) believes, makes the model better adapted to the context in which it is used. Prompt engineering is also a key factor and by formulating clear and structured instructions to the model, incorrect responses can be reduced. In addition, the importance of using structured APIs and controlled data sources, rather than free text prompts, in applications where precision is crucial is emphasised. Finally, the need for model monitoring and evaluation over time is also highlighted, to continuously detect and adjust for systematic errors or changing conditions. The solution to hallucinations requires a combination of technical architecture, human control and data quality, with each component contributing to making generative AI more reliable in practice (Tancredi, 2024).

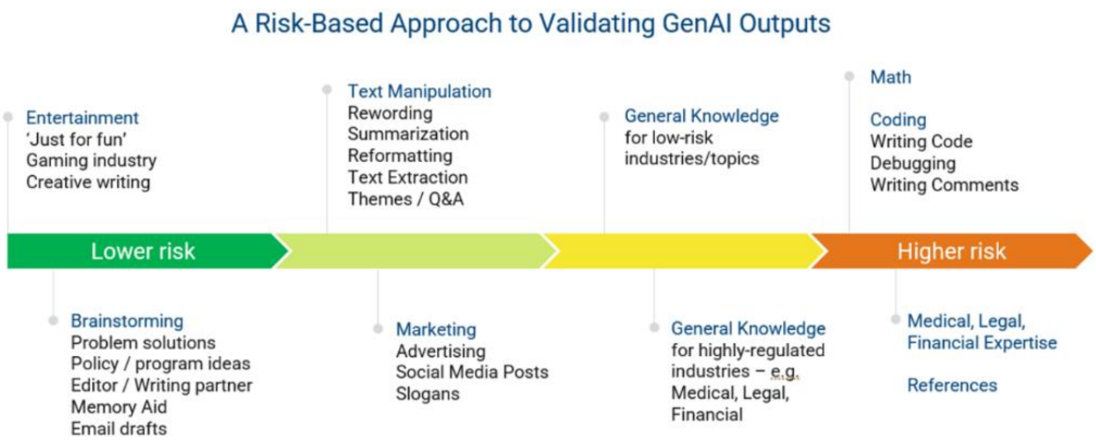

Figure 5: Validating the risk for generative AI outputs (Tancredi, 2024)

That generative AI is not equally reliable in all contexts is illustrated in figure , which presents a risk-based approach to validating AI-generated results. At the starting end of the risk scale, the consequences of possible errors or hallucinations are generally limited, and generative AI can function as a productive support without much verification. Further towards the middle of the scale, errors can be more problematic but still manageable with human review. At the end of the scale, not only technical precision is required, but also a high degree of responsibility and transparency. The risk of incorrect output having negative consequences is significantly higher, especially in highly regulated sectors (Tancredi, 2024).

The model underlines that validation and control of AI output must be adapted to the area of use, and that generative AI should be used with particular caution in areas where errors are not only costly but potentially harmful. It can therefore serve as a guide for how and where AI can be implemented in practice and where human expertise remains absolutely crucial (Tancredi, 2024).

3.4.2 The black-box nature of generative models

Generative AI tends to act as a black box, which raises challenges around transparency in the models. This can make it difficult for the users to understand or track how the model arrived at a certain answer (Mohamed Shaffi, 2024). This creates problems when decision support needs to be auditable or justified, especially in regulated or sensitive decision-making environments.

To address these transparency problems, a number of technical solutions have been developed. An important category is so-called Explainable AI (XAI) techniques that make the behavior of models more interpretable. Explainable AI tools offer visualisation and diagnostics that help users understand why the AI model gave a certain answer (Mohamed Shaffi, 2024). Such tools can be integrated into analysis workflows and thus enable a more informed and critical review of the AI's recommendations. However, it is important to emphasise that explainability is not only a technical issue, but also requires training of users to be able to interpret and act on the explanations (Mohamed Shaffi, 2024). Yampolskiy (2025) draws attention to the need for a broader perspective on observability, that is, the ability to continuously monitor, understand and predict the behavior of the AI system in practice. Many generative AI models today are not only difficult to interpret, they are also difficult to observe, especially when unexpected or emergent behaviors arise. Building trust and accountability thus requires not only an explanation of individual decisions, but also continuous analysis of how the model behaves as a whole (Yampolskiy, 2025).

3.4.3 Data challenges: structure, semantics and quality

In addition to model-related limitations, there are also technical challenges related to the data itself that generative AI relies on. Models are highly dependent on being trained and working with high-quality, structured and semantically clear data. Incomplete definitions, inconsistent concepts or fragmented data sources can severely reduce the quality of the generated output (Wamba-Taguimdje et al., 2020).

To ensure a structured, systematic and secure handling of data in a larger organisation, data governance takes on an important role. With the aim of guaranteeing a certain quality, security and compliance with laws and regulations, data governance is used to establish policies and processes to fulfill it (Khatri & Brown, 2010). Along the same lines, Otto (2011) defines data governance as a set of strategies and structures for managing data in a way that maximises value while minimising risk. By effectively managing data, organisations can ensure reliable and consistent use of data, which Otto (2011) considers crucial for data-driven decision-making and the implementation of advanced analysis methods such as generative AI.

3.4.4 Technical AI readiness

Another key issue is the organisation's technical readiness, or AI readiness. This refers to the degree to which the organisation has the right infrastructure, data quality, access and metadata to use AI effectively and safely. Models such as the CBDAS AI readiness framework offer structured methods for identifying strengths, gaps and areas for improvement prior to AI implementation (Malacaria et al., 2023). The CBDAS framework, which stands for culture, business, data, analytics and strategy, helps organisations assess their readiness across these five dimensions, ensuring that AI initiatives are aligned with strategic goals, supported by a data-driven culture, and grounded in robust analytical capabilities. By systematically evaluating each domain, CBDAS enables decision-makers to prioritise investments and interventions that enhance overall AI maturity and increase the likelihood of successful adoption.

In practice, a combination of measures is required, where on the model side investments are needed in explainable interfaces, version control and output validation. In terms of data, organisations need to introduce common definitions of concepts, ensure data quality and clarify data ownership, not only for content, but also for semantic usability. Malacaria et al. (2023) finally says that organisations at the system level should use AI-readiness frameworks to ensure that the infrastructure and skills are sufficient to support the technology.

3.5 Challenges and enablers of AI adoption in an organisational context

Within the TOE framework, the organisational context captures internal factors such as managerial structure, resources, degree of centralisation, scope and size of the organisation (Abu-Khadra & Ziadat, 2012). These factors influence an organisation's readiness and capability to support technological innovations which makes the organisational dimension of the TOE framework essential for understanding both enablers and barriers of effective integration of generative AI.

3.5.1 Strategic alignment

The art of managing data effectively is a key for competitiveness and generative AI offers several opportunities to streamline complex analytics processes and enhance decision-making. At the same time, this transformation presents organisational challenges that extend beyond technical integration (Al-kfary, 2015). Managing information in new ways means organisations need to change how they think, operate and build their skills (Wamba-Taguimdje et al., 2020).

One of the central challenges is the need for strategic alignments between AI initiatives and the organisation's overall business objectives (Al-kfairy, 2025). In large enterprises, AI solutions must not only function technically but also contribute to long term value creation across various domains. According to Al-kfairy (2025), this requires cross-functional collaboration between departments to ensure that generative AI solutions are integrated in a coherent and business-aligned way. Cross-departmental collaboration between functions such as IT, legal, compliance and business units is also important for identifying use cases, managing risks and implementing governance structures. This collaboration helps ensure that generative AI applications are ethically, legally and operationally aligned with the organisation's values and regulatory requirements (Schneider et al. 2024).

3.5.2 Change management

Change management is another critical factor when implementing generative AI, as it helps organisations navigate both technical and cultural transformations (Al-kfairy, 2025). When introducing new technologies, not only already existing technical systems are affected, but also working methods, decision-making processes and the organisational culture which can result in employee resistance (Al-kfairy, 2025). Change management is about ensuring that this transition takes place in a structured and effective way by preparing, supporting and implementing the change in a way that reduces resistance and increases acceptance (Kotter, 1996; Hiatt, 2006). Al-kfairy (2025) highlights the importance of transparent communication regarding the role of AI and also continuous training programs to ensure that employees across different functions can understand and effectively use AI tools.

There are a number of frameworks within change management with the aim of understanding and managing technical changes. One of the more established is Kotter's 8-step process for leading change. The change process is divided into steps from creating a need for change and anchoring it long-term in the organisational culture (Laig & Abocejo, 2021). This model emphasises the importance of communicating a vision, involving key people, creating early successes and ensuring that the change becomes a natural part of the organisation's structure. Another model is Lewin's 3-stage model of change which describes a change as a three-phase process: thawing, changing and refreesing. The thaw phase aims to create awareness of the need for change, the change phase involves the implementation of new ways of working and the refreese phase is about combining the change as part of the organisation's standardised processes (Lewin, 1951). According to Hiatt (2006) the ADKAR-model can also be relevant in the case of technological changes such as the implementation of generative AI. The model focuses on change from the individual's perspective and describes five key components required for a change to succeed. These include awareness of the need for change, willingness to participate in the change, knowledge of how the change is implemented, ability to apply it in practice and reinforcement to sustain the change over time.

In the context of generative AI, effective change management is essential, as this technology can reshape roles, automate tasks, and influence decision-making. Without a structured change process, organizations risk employee resistance, inefficiencies, and fragmented AI strategies, leading to poor outcomes and diminished trust in AI systems. Applying Kotter's model can help build organizational readiness for AI, while Lewin's model supports gradual implementation. The ADKAR model can be used diagnostically to identify and address individual-level barriers through communication, training, and follow-up (Hiatt, 2006).

3.6 Challenges and enablers of AI adoption in an environmental context

The environmental context refers to the external factors that influence an organisation's decision to adapt a new technology. These include industry trends, regulatory requirements, resources, suppliers and other actors (Tornatzky & Fleischer, 1990). Organisations do not operate in isolation, they function in environments that are constantly evolving due to technical advances, shifting market demands and changes in the regulatory landscape. Tornatzky and Fleischer (1990) explain how the environmental context presents both opportunities and limitations for technology innovation. Key actors within the industry can support innovation by providing critical information, resources and legitimacy. At the same time, these stakeholders may also impose limitations through regulatory frameworks, policy restrictions, or limited access to capital. An organisation's relationships with these external actors can significantly influence its ability to effectively adopt and implement new technologies in a way that aligns with both its goals and the external demands (Tornatzky & Fleischer, 1990).

3.6.1 Ethical considerations in data-driven environments

Ethical issues are often discussed in connection with the introduction of new technologies. Generative AI raises several ethical challenges, including data privacy, copyright issues, algorithmic bias and a lack of transparency in decision-making (Al-Kfairy et al., 2024; Feuerriegel et al., 2024). These issues can lead to reputational, legal and operational risks if not properly addressed.

Al-kfairy et al. (2024) underscore the importance of establishing robust ethical frameworks for the responsible development of AI, prioritising the principles of human rights, fairness and transparency. Promoting transparency and accountability in AI systems is essential, requiring the disclosure of datasets and algorithms used, as well as regulations to prevent the spread of false information. Encouraging collaboration among policymakers, technologists and researchers from various fields can ensure that diverse perspectives are considered in ethical discussions. This dialogue can help identify best practices and innovative solutions to mitigate ethical risks. Additionally, it is important to continuously review and update ethical frameworks to address emerging challenges as the technology evolves (Al-kfairy et al., 2024).

Kirova et al. (2023) discusses similar ethical concerns but believe that rather than advocating for restricting or abandoning generative AI, there should be a focus on ensuring its responsible and ethical use. This balanced perspective acknowledges both the opportunities and risks associated with AI, reinforcing the importance of ethical oversight while allowing society to harness its full potential (Kirova et al., 2023).

3.6.2 The regulatory landscape of generative AI

Tornatzky and Fleischer (1990) highlight external regulations as an important environmental factor that affect the search for and adoption of new technologies. Laws and regulations can both hinder and stimulate innovation (Tornatzky & Fleischer, 1990). The legal and regulatory landscape for generative AI is characterised by uncertainty, divergence and ongoing development (Schneider et al., 2024). Schneider et al. (2024) highlight that different countries adopt diverse approaches to AI regulation. For example, some nations implement sector-specific (vertical) regulations targeting particular applications, such as healthcare or finance. Others, like the European Union, have introduced comprehensive horisontal laws such as the EU's AI Act. The EU's proposed regulation aims to establish a broad legal framework governing the development and use of AI systems, specifying requirements related to transparency, safety and accountability. However, the regulatory landscape remains highly dynamic and fragmented, with ongoing debates regarding issues such as liability, data privacy, intellectual property rights and safety standards. Schneider et al. (2024) notes that regulation currently provides limited guidance on managing AI-specific risks, especially regarding generative models capable of producing incorrect or harmful content.

4. Methodology

The following section outlines the study's methodological approach. It begins with a discussion of the qualitative research design and the rationale behind the chosen method. Next, the data collection methods are presented. Finally, the ethical considerations relevant to the study are discussed as well as the study's credibility.

4.1 Qualitative research strategy

In social research, the relationship between theory and empirical data can follow different approaches that determine how researchers engage with existing theories and empirical observations. A deductive approach begins with a pre-established theoretical framework from which hypotheses are formulated. These hypotheses are then tested through empirical observations to confirm or reject the theory (Bryman, 2016). An inductive approach, on the other hand, builds theory from observations and collected data. Theories emerge as patterns and relationships are identified within the data (Bryman, 2016). A third approach, abduction, combines elements of both deduction and induction Clark et al. (2021). Researchers begin with a theoretical foundation relevant to the studied context but remain open to adjusting and refining it based on empirical findings. This interplay between theory and data is particularly useful when studying dynamic environments such as large organisations.

Furthermore, this study adopts a qualitative research strategy to explore the role of generative AI in transforming analytics workflows. In contrast to quantitative research, which focuses on measurable and statistical analysis, qualitative methods focus on understanding phenomena through subjective experiences and meanings (Bryman, 2016). It relies on textual data, which must be systematically organised and analysed. As Yin (2016) highlights, the main goal is to order and structure the data in a meaningful way to ensure thorough analysis. A qualitative research design is particularly suitable for this study as it provides expert perspectives and experiences of both the opportunities and challenges associated with integrating generative AI into analytics processes.

Within qualitative research there are a variety of different methods including observations, qualitative interviews, focus groups, discourse analysis and text analysis (Bryman, 2016). Each of these methods offers different strengths depending on the research question and the nature of the data being explored. It is not uncommon to combine these methods to enrich the data collection process. The chosen method in this study is qualitative interviews, more specifically semi-structured interviews.

4.2 Qualitative interviews

According to Yin (2016) all forms of interviews fall into either of the two categories structured interviews and qualitative interviews. Structured interviews follow a scripted interaction where the interviewer asks a standardised set of questions from a formal questionnaire. The interviewer maintains consistent behaviour throughout all interviews to ensure a uniform data collection. These interviews typically use closed-ended questions, making them common in surveys and polls, which aim for representative samples and statistical analysis. Structured interviews differ from qualitative interviews but can be part of mixed methods studies if combined with qualitative techniques. Qualitative interviews are more flexible, conversational and open-ended. Instead of following a strict script, Yin (2016) explains that researchers adapt the questions based on context which creates a social relationship with the participants. Bryman (2016) describes how an interviewer can choose to deviate significantly from the prepared questions to explore relevant themes or respond to unexpected insights that emerge during the conversation. These interviews focus on understanding participants' experiences and unlike structured interviews, which prioritise consistency and closed-ended questions, qualitative interviews aim to capture deeper meanings (Yin, 2016).

One type of interview that falls under the concept of qualitative interviews is the semi-structured interview (Bryman, 2016). Semi-structured interviews are a flexible and commonly used method in qualitative research (Bryman, 2016), allowing for guided conversations while still providing room for participants to share their unique insights. The possibility of adapting the interview questions according to the respondent's answers made this method particularly appropriate for exploring the respondent's personal experiences, attitudes and perceptions regarding the implementation of generative AI. This adaptability ensured that the interview could dive deeper into relevant topics as they emerged, capturing different perspectives and providing data for understanding the complexities involved in integrating generative AI into analytics workflows.

4.3 Choosing respondents

When doing qualitative research based on interviews, the interview participants play an important role and selecting relevant respondents is therefore crucial for the study. When choosing potential interviewees, the primary consideration should be to determine who has the knowledge and experience to answer your questions or provide the insights you need (Rowley, 2012). This approach is referred to as "purposive sampling" and involves deliberately selecting participants based on their relevance to the study, rather than selecting them randomly (Silverman, 2010).

For this study, a few respondents were initially selected based on their knowledge and involvement in the different stages of the analytics workflow. To further expand the sample and ensure a diverse range of perspectives, some of the respondents were chosen through the snowball sampling method. Snowball sampling is a method where the researchers let previous interview participants propose future possible respondents

(Bryman 2016). The combination of purposive sampling and snowball sampling ensured that the interviews provided valuable insights and captured important information needed for the purpose of this study. A total of seven interviews were conducted, of which one was conducted with three people at the same time. All respondents are presented in Table 1, together with, date, duration and the focus areas.

Rowley (2012) further emphasises that the selection of respondents also depends on willingness and availability to participate. The initial approach is crucial as they will quickly decide if they want to participate or not. It is important to introduce them to the research and explain the purpose. The researcher should also specify the interview's duration, request permission to record and assure confidentiality. All respondents in this study were asked via email to participate. The email included a short explanation of the study, the focus areas for the interviews and suggestions of time. Permission to record was obtained at the time of the interview.

Respondent	Description	Duration	Format	Date
Respondent A	Product line manager – enablement platforms	30 min	Interview (in person)	12/2 - 25
Respondent B	Product area manager – enablement platforms	40 min	Interview (in person)	13/2 - 25
Respondent C	Technology architect	40 min	Interview (teams)	14/2 - 25
Respondent D	Product line manager – AI analytics	30 min	Interview (teams)	27/2 - 25
Respondent E	AI & analytics specialist	45 min	Interview (teams)	5/3 - 25
Respondent F	Data engineer	45 min	Interview (teams)	11/3 - 25
Respondent G	Head of site material	40 min	Interview (in person)	20/3 - 25
Respondent H	Regional supply planner	40 min	Interview (in person)	20/3 - 25
Respondent I		40 min	Interview (in person)	20/3 - 25
Respondent E	AI & analytics		Follow up questions	27/3 - 25

	specialist		(email)	
Respondent F	Data engineer		Follow up questions (email)	27/3 - 25

4.4 Interview preparation, execution and analysis

In preparation for the semi-structured interviews, an interview guide was designed in alignment with the study's purpose and research questions. A few important topics were identified, such as understanding the current analytics workflow, identifying bottlenecks and challenges, potential for generative AI in analytics and AI implementation and adoption challenges. A set of interview questions was formulated with the use of these topics. The questions were designed to be somewhat flexible, allowing for adjustments based on expertise and professional background of each respondent.

The interviews were held in-person or digitally depending on the respondent's availability and current location. All interviews were recorded after assuring permission from the respondent and the recordings were later transcribed. Yin (2016) explains that while the process of reviewing recordings can be time consuming, it is often very valuable for the study. The act of transcribing recordings can start the analysis process, as researchers engage with the data, identify important contextual details and start to develop initial insights (Cope, 2020). Cope (2020) states that "doing one's own transcribing also serves as a strong first-round analysis exercise".

To ensure a structured and insightful analysis, the transcriptions were carefully reviewed. Following Braun and Clarke's (2006) thematic analysis approach, the data was systematically organised by identifying patterns and assigning codes to different segments. These codes were then grouped into broader categories, helping to uncover recurring themes and significant insights. The themes that structure the results in chapter 5 emerged during the process of analysing the data. Organising the findings in this way provided a better understanding of generative AI's role in the analytics workflow. This approach also made the analysis more structured and clear, allowing for meaningful connections between respondents' perspectives.

After reviewing the interview material, two respondents were contacted a second time via email for a number of follow-up questions. The reason for this was to get a more detailed explanation of some concepts and to explore certain questions that were raised during the review.

4.5 Ethical considerations and awareness

Taking ethical aspects into account is important to ensure responsible research. Bryman (2016) discusses four ethical concerns identified by Diener and Crandall (1978); harm to participants, lack of informed consent, invasion of privacy and deception. To avoid potential harm the respondents were assured that their participation was voluntary. The interview questions were also sent in advance, which gave the respondent the opportunity to prepare and also indicate if any topics were irrelevant or uncomfortable to discuss.

Informed consent is fundamental in ensuring that participants are fully aware of the study's purpose, their involvement and any potential risks. Before the interviews, participants were provided with a clear explanation of the study, the interview topics and the recording procedures. This information was given in the initial email and again at the time of the interview. To protect participants' privacy, all responses were anonymised and no directly identifying details were included in the final report. Confidentiality was maintained by securely storing interview data and ensuring that only authorised researchers had access to it. The recordings were deleted after the thesis was completed.

Since qualitative research involves analysing subjective data, it is also important to recognise that responses can be interpreted in different ways. To ensure accurate representation of participants' perspectives, the data was carefully reviewed and coded to reduce researcher bias.

4.6 Methodology discussion

In all types of research it is important to have a discussion about credibility and quality. In quantitative research the criteria of reliability and viability is widely used, however evaluating the quality of qualitative research presents unique challenges. While some scholars have attempted to apply the concepts of validity and reliability from quantitative research to qualitative studies, others argue that these terms are not entirely appropriate due to differences in research approaches (Bryman, 2016). Instead, the term trustworthiness is proposed as a way to determine the quality of the study.

Trustworthiness consists of four key criteria; credibility, transferability, dependability and confirmability. To enhance credibility, this study used a systematic thematic analysis approach to ensure that patterns were derived from the data rather than researcher assumptions. Additionally, respondents from different roles within the analytics workflow were included to capture a broad range of perspectives. Transferability refers to whether the findings of the study can be applied to other contexts (Bryman, 2016). Therefore, information about the context in which the study operates is provided in the report and what the specific case is.

Dependability relates to the consistency of the research process (Bryman, 2016). To ensure dependability, all methodological choices, interview questions and data analysis steps were documented and presented in the final report. This allows future researchers to understand how conclusions were reached and enhances the study's reliability. Finally, to achieve confirmability, both authors of this study participated during the interviews but went through the recordings separately to avoid influencing each other's interpretation of the material.

5. Results

The following section presents the results of interviews conducted with key people within Ericsson who work with or are affected by data management, analytics and generative AI. The results show both the perceived benefits, challenges and future opportunities linked to the use of generative AI in the organisation's analytics workflow. Thematically, the results have been divided into six main areas*: Streamlining workflow with generative AI, Structuring of data, Organisational complexity and governance, Not the tool for every problem, Trust, security and compliance* and *Human-AI collaboration*.

5.1 Streamlining workflows with generative AI

In the interviews, generative AI is considered to have the potential to reduce the time for all stages of the analytics workflow, data collection, data preprocessing, visualisation and reporting. There is a consistent insight among respondents that although the technology offers great benefits, the right conditions and skills are required to fully benefit from its potential. Respondent F, working as a data engineer, highlights that AI has led to a significant reduction in the time spent building pipelines and writing SQL code for data collection:

> *"Building a pipeline used to take me one week, now it takes me three days, sometimes less than two days"* (Respondent F, Data engineer).

However, it is not just about getting the AI to write code. Respondent F highlights the importance of giving the right instructions and understanding the underlying logic, otherwise the work risks becoming ineffective: *"You have to give it a skeleton and then you have to give it small prompts, and you must have expertise"*. Respondent A, a product line manager working within product enablement also mentions this: *"I don't get much time to code, but when I do, it's easy to go into the chat and get help with what to do, and it can even write the code for you"*. While respondent F acknowledges the need for guidance and structure, he also notes that the importance of precise prompt engineering has slightly decreased as the models have improved. According to him, what matters more now is clearly communicating the desired outcome, rather than crafting complex or detailed prompts: *"It's more about giving the AI a clear direction, what you want it to achieve, rather than knowing exactly how to ask"*.

Several respondents point out that generative AI can be used to automate parts of data collection and data preparation. Respondent F mentions that they already have agents that automatically start processes in data collection and sees opportunities to delegate even more of the work to generative AI in the future. He sees a future where AI will increasingly drive data collection based on business needs.

> *"For data collection you can have agents to automatically start the machine. It's not something new but has been happening for the past 6-7 years. I've been doing that myself"* (Respondent F, Data engineer).

Respondent E, working as an AI and analytics specialist, also sees the potential in letting generative AI identify what data is needed and control the collection accordingly. He believes that this can lead to a more dynamic and needs-driven data collection, rather than working from predefined datasets. He says: *"We want AI to understand the business logic and retrieve the data needed for the analysis itself".* At the same time, respondents emphasise that the automation of collection and integration requires a robust framework for data quality and governance. Without a solid foundation, AI risks working from incorrect or inconsistent data, which can lead to invalid decisions.

There is also potential to change how data is visualised and reported, which is emphasised by respondent G, working as head of site material. Respondents describe how future reporting could increasingly be interactive and driven by users' needs in the moment, rather than through fixed dashboards. Respondent D, a product line manager within AI analytics says: *"Reporting will change. You won't need dashboards, you will talk directly to the data".* Furthermore, respondent E describes how AI can create customised reports and visualisations in real time, based on the user's questions and needs, he says: *"Why should I build a Power BI dashboard when AI can do it for me on the fly?".* He believes that people are still in a dashboard mindset and that analytics means dashboards for many and says:

> *"And there is also a perception that analytics = dashboard. As with all examples, the mental image within IT still revolves around dashboards. So if someone wants to perform more advanced analyses, that possibility isn't even part of the mental map. As a result, all information is structured based on that limited view"* (Respndent E, AI & analytics specialist).

He further believes that the ability to ask direct questions to an AI will remove the purpose of dashboards but that the structure of the data puts some constraints on it. A challenge noted by another respondent is the complexity of current dashboards. Respondent G explains that conflicting visualisations and information overload can lead to cognitive fatigue for users.

> *"They are all saying the same things but in different ways. [...] The amount of time or the amount of training that we have to have to use some of these visualizations because we either overcomplicated to the point that they are specific dashboard for one person only. Or there's so much in them that it becomes impossible to get to the level that you need to make your decision"* (Respondent G, Head of site material).

He believes AI tools could simplify this experience by restructuring dashboards to highlight only the most relevant and actionable insights. At the same time, respondent F highlights the creative possibilities of AI in dashboard design: *"I was able to create such beautiful graphs, that would take you a week to make in other programs".*

When it comes to decision-making, AI has the potential to automate certain steps, particularly in routine approvals. Respondent G described how many decisions are currently reviewed in meetings that could be streamlined by AI, reducing the need for excessive discussions and allowing employees to focus on other tasks. *"There's a lot of meetings that could probably be emails, which could also probably be decisions made by a tool"*. Even if generative AI can function as a support for decision-making, respondent A argues that AI is not yet capable of independently making decisions, as it lacks the depth of reasoning and contextual understanding that complex decisions often require. Respondent G also emphasises that while AI can provide recommendations, final decisions often still require human approval, especially in high-stakes scenarios. In cases where standard conditions are met, employees may not mind whether a human or an AI system confirms the decision. However, for more complex and critical business choices, human oversight is still considered essential.

5.2 Structuring of data

It is emphasised by respondent E that the primary challenge in supply chain analytics and AI-driven data retrieval is not the technology itself, but the fundamental structuring of data. He explains the analytics workflow by presenting an example of a process for analysing where to put a new storage. The respondent explains that modern analysis tools require a certain data structure that is currently lacking within the organisation.

> *"All the tools on the market ask you to fill in your locations, fill in your products, and specify how material should flow from point A to point B. That's basically the foundation of how you input the data"* (Respondnet E, AI & analytics specialist).

An examination of the existing master data reveals several gaps:

> *"Do we have the concept of location in our master data? No, we don't. OK, that's a bit of a problem. Do we have a hierarchy for the products? No, there are many different ones, so we might be able to reuse something someone else has done, but there isn't a common numerical one we're supposed to use"* (Respondent E, AI & analytics specialist).

As a result, a substantial amount of work is required to restructure and collect the necessary data before any in-depth analysis, particularly cost-related, can be carried out. The historical development of the organisation's datasets further contributes to the issue. The data has been structured primarily to answer isolated operational questions rather than to support broader analysis:

> *"We've built datasets that are designed to give an operational description of a specific site. That's interesting if I only want to look at a single site in isolation [...] but if I want to go further and do a tactical or strategic analysis? That's when we run into big problems"* (Respondent E, AI & analytics specialist).

To fully leverage AI for analytics, the respondent explains that businesses must prioritise structuring their data in a way that facilitates automated querying and intelligent data collection. By proactively defining data relationships and integrating business logic, he believes that the organisation can move towards more advanced, AI-assisted decision-making, ultimately bridging the gap between operational reporting and strategic analysis.

Respondent F, the data engineer, points out that a lack of unified data definitions across departments further complicates the analytics process. Working across different markets makes it difficult to achieve a coherent organisational view and he says:

> *"5 market areas means there are multiple business users. Each has different requirements. Everyone wants their dashboard to look perfect from their end"* (Respondent F, Data engineer).

This means that a lot of work is required to harmonise needs and create common solutions that work for the entire organisation. According to respondent F, the real challenge lies not in the technical implementation, but in gathering, understanding and translating diverse business needs into a shared, codable structure. This is also noted by respondent E, who states that a disproportionate amount of time is dedicated to preparing data before analysis can even begin. He estimates:

> *"90 percent of the time is spent structuring the information we have and then taking in the information we don't have, information about master data that we lack"* (Respondnet E, AI & analytics specialist).

Data processing is thus repeatedly identified as one of the most resource intensive stages of the analytics workflow. According to respondent C, working as a technology architect, inefficiency is closely tied to how data is originally structured. He explains:

> *"The data is structured to answer operational questions. That's where we run into problems when we want to move away from point-by-point analysis and towards a more strategic analysis"* (Respondnet C, Technology architect).

Respondents also highlight the importance of collaboration to achieve a common understanding of data and analysis goals. Respondent C sees the lack of coordination as one of the biggest bottlenecks in today's analysis work an says:

> *"We need to think in horisontal frameworks and enablers. [...] If everyone does everything from scratch, it will be very cumbersome. [...] Oh, I take this decision here, but another decision is taken based on the same data here. So, what should we trust?"* (Respondent C, Technology architect).

5.3 Organisational complexity and governance

A recurring topic in discussions about challenges was the organisation's size and complexity. Respondent B, a product area manager within enablement platforms, describes it as:

> *"a combination of two things. One is the size of it, but also we are not like a greenfield setup, we have a brownfield setup which means we have a big legacy from multiple perspectives"* (Respondent B, Product area manager within enablement platforms).

Meaning that with a brownfield setup, older technologies are still being used simply because people rely on them, which makes it harder to modernise. He proceeds by showing a map of the organisation's tools, a way to illustrate the ecosystem of systems and processes he previously described as complex. He says:

> *"If I was starting my own company now and I had to start from scratch I would not go with 90 tools, I would probably go with 5. But you don't have that kind of luxury unless you are working in a startup or a small company"* (Respondent B, Product area manager within enablement platforms).

The interviews show that the analytics workflow today is characterised by complexity, manual processes and high demands on coordination. Since the process stretches across several business areas, all with their own goals and needs, aligning around shared solutions becomes difficult. Respondent F describes it as a chain of interdependent steps where everything needs to function for the workflow to deliver value. He says that:

> *"The hard part is not writing the SQL code, it's getting everyone to agree on what is actually to be measured"* (Respondent F, Data engineer).

Respondent E highlights how the belief that only IT understands the data leads to a centralised approach to analytics. As a result, data-related tasks get stuck in queues, and by the time answers are delivered, the original business questions might no longer be relevant. Even when access is granted for innovation purposes, employees often face internal processes designed for stability in production, not experimentation.

The respondent further explains that even when the data and appropriate tools are available, transferring data between systems requires complex approval processes. He says:

> *"The data is in the database, and you've structured it well. But you don't have a good computational engine within the database [...] So you need to move the data. Then it has to go through a data transfer approval process, where you have to review each individual data element, who owns it? Then get approval from the owner to transfer the data"* (Respondnet E, AI & analytics specialist).

He describes the situation as frustrating and points to the internal culture as a major barrier to innovation. *"The processes are optimised for stability and control rather than for learning and experimentation,"* he says, highlighting how existing routines and approval chains are designed to minimise risk rather than support agility. Importantly, he notes that this mindset does not come from formal leadership directives, but is embedded in the way people work and think across the organisation. As an example, he adds*: "There is a culture that my data is sensitive [...] and people overestimate their own database sensitivity."* This tendency to treat data as proprietary or high-risk, even when it may not be, reinforces silos and slows down cross-team collaboration and experimentation.

Respondents A and B, both in more managerial roles, also point out the need for better communication and collaboration across teams. They raise the concern that different departments may make different decisions based on the same data. To avoid this, both say that there needs to be a shared understanding of business logic and data semantics across the organisation.

5.4 Not the tool for every problem

A key theme that emerged during the interviews was that generative AI is not the best solution for every problem. Respondent B, the product area manager, emphasised the importance of using the right technology for the purpose rather than treating generative AI as an universal solution. He points out that generative AI can be resource demanding and expensive, making it crucial to evaluate its applications in the analytics workflow. He explains:

> *"The other risk is that not everything is a generative AI problem and generative AI is also expensive. So in my job it is more about using the right weapon for the right problem"* (Respondent B, Product area manager within enablement platforms).

Furthermore the respondent highlighted a tendency to adopt generative AI simply because it is a trend and not because it is the most effective solution. There is sometimes a perception that analytical work must involve generative AI to be considered valuable, which the respondent thinks is misleading. In some cases, simpler technologies, such as rule-based automation may be more suitable. Respondent B says:

> *"It is about using a fit-for-purpose technology. Not everything is going to be genAI, not everyone wants to have everything AI. Maybe some of the use cases can be done with a simple workflow ruleways automation"* (Respondnet B, Product area manager within enablement platforms).

The data engineer, respondent F, gave an example of a task that took several hours longer with the use of generative AI, also noting that it is not a tool for every problem. Respondent B believes that instead of focusing solely on generative AI, the organisation should view it as a part of a toolkit and select different tools depending on the characteristics of the problem.

It is considered important to avoid over engineering and to not complicate things that do not create value. There is no point in putting generative AI into simple cases that can be solved using simple SQL and respondent F sees it as a recurring problem with all new technology where humans tend to get overly excited, causing complications. He believes that for generative AI it is still time for it to mature, not as a technology but in its usage.

5.5 Trust, security and compliance

A recurring theme in all interviews is the issue of trust, security and compliance when using generative AI in analytics. Respondents agree that AI offers great opportunities, but that the prerequisite for being able to benefit from these is that one can trust both the quality of the data and the reliability of the AI models.

Several interviewees express caution about relying on AI generated insights. Respondent A says that *"you can never trust it [...] to be able to get the right help you need to ask the right questions"*. He highlights the importance of being careful when interpreting responses generated by AI and explains that they should be compared to other models' results. In a global and complex organisation, data security is seen as especially critical. Respondent D, a product line manager within AI analytics explains that:

> *"The biggest risk is that you need to have the right compliance and security around it. A wrong insight or output can be handled and it is not such a big risk, but the risk of someone outside coming in and changing the data leading to wrong advice or results is bigger"* (Respondnet D, Product line manager within AI analytics).

Others, such as respondent E take a different view, arguing that concerns around bias and security are sometimes overstated, leading to over-bureaucratisation that hinders innovation. He believes that fear around AI and restrictive data policies prevent experimentation and that organisations must create space for employees to explore generative AI in order to unlock its full potential.

> *"I'd say there's too much focus on security, and bias, and those kinds of issues. [...] We're starting a bit too much from the bureaucratic end, instead of letting users in early and learning from them, how they use it and what challenges they encounter"* (Respondent E, AI & analytics specialist).

In this context, the concept of explainable AI (XAI) was also briefly discussed. Respondent E has encountered XAI as a concept but notes that attempts to implement it have been limited, primarily due to cost. Instead, he emphasises the importance of AI observability and monitoring as practical ways to enhance transparency, security and trustworthiness in deployed models. Meanwhile, respondent F says that he is not familiar with XAI specifically, but emphasises that trust in AI is often linked to the specific task the system is used for. When the task is complex or the AI's reasoning is difficult to understand, people are naturally more hesitant to rely on its output. This highlights the importance of transparency and human oversight, especially in high-stakes situations.

5.6 Human-AI collaboration

All respondents agree on the need for humans to have the final responsibility when interpreting results and making decisions, even if generative AI can offer strong support. Respondent E raises the risk of relying too much on automated insights, which can lead to poor decisions if the information isn't properly validated, *"We have to keep people in the loop, even if AI does the heavy lifting. It is still our responsibility to make the right decision"*.

Respondent F sees potential for AI to take a more active role in decision support in the future, not only by delivering analysis but also by automatically identifying risks or opportunities and triggering actions in response to certain business events. Still, human oversight will be necessary to ensure those actions align with the bigger picture. This balance between automation and human judgement was echoed by others. As respondent B says:

> *"The problem is that we tend to overestimate the technology sometimes and neglect the human aspect or team aspect of it"* (Respondent B, Product area manager within enablement platforms).

Similarly, respondent G noted that

> *"I think there will always be some level of human involvement, even if that human involvement is the rubber stamp"* (Respondent G, Head of site material).

In addition to having the final say, human expertise is also crucial throughout the process. Respondent F points out that AI systems need to be trained to understand our language and our way of working. He explains that the AI usually needs a basic structure to work from, and that it's up to the user to modify and fine-tune it so that the output is correct and useful. It's important to be involved in the process to understand what the AI is doing and be able to tweak the output if needed, *"The point I am trying to make is that generative AI is involved, but with human effort. Hand in hand."*. He believes that today, development hasn't come far enough for someone to simply ask the AI for SQL code, plug it into a pipeline and run it without checking. He doesn't know if that will be possible in the future or not, but for now, human involvement is still crucial. Respondent G, however, does not see a future where generative AI operates freely throughout the entire process. He says:

> *"I don't necessarily know that you'll ever have a scenario in a company that is as R&D and engineering focused as we are, where it will ever just let the machine run the thing all the way in front to back. [...] Like we have relations with the customer. And so we kind of know the expectation of how they will change. And so it's like to a point, AI can take some work off it and*

suggest things. [...] But there will always be humans. Just we know how they work and we know how they operate" (Respondnet G, Head of site material).

6. Analysis

The purpose of this thesis is to explore the role of generative AI in analytics workflows, assessing where and how it can be implemented to enhance efficiency and decision-making within a large, globally operating company. To answer this, the following chapter analyses the empirical material in relation to the theoretical framework. The analysis is structured according to the TOE framework (technology, organisational and environmental) and based on the three types of decisions: operational, tactical and strategic.

6.1 The role of technology in AI-supported analytics

6.1.1 Boosting productivity through automation

A recurring theme in the interviews is how generative AI enables efficiency gain by automating repetitive and manual steps in the analytical workflow. Respondents describe how the technology is used to generate code, start data collection processes and create reports. This type of automation has the greatest impact on the operational level, where, for example, one respondent describes that a task that previously took a week can now be completed in less than two days.

Based on the interview responses, it can be concluded that efficiency is not only about faster execution, but also about changing the nature of the work. It appears that several respondents feel that generative AI frees up time that was previously spent on repetitive tasks, which in turn opens up for more analysis, reflection and proactivity. This means a shift from operational to strategic focus, where analysts can put more energy into interpreting results and contributing to long-term decision-making. The material suggests that future analytics will be less static dashboards and more interactive dialogue, where users can ask questions of the data in real time and receive customised answers. This could ultimately enable faster and more situational insights, which strengthens the conditions for more data-driven decision-making.

At the same time, the interviews show that the strategic benefit of AI depends on various factors. Several respondents highlight that for these tools to function as support for higher level decisions, both technical maturity among the users and a structured data basis is required. One of the respondents expresses that the model needs to be given a code skeleton, which suggests that generative AI cannot act autonomously, but needs guidance and context. This is emphasised by Tancredi (2024), mainly in the context of hallucination, who believes that the solution to making generative AI more reliable is based on a combination of technical architecture, human control and data quality. At present, there seems to be a clear gap between the technical capabilities of generative AI and the users' actual working methods and ability to fully utilise the tools.

It can be seen that generative AI has started to deliver operational gains within parts of Ericsson, particularly by speeding up coding, reporting and data collection. However, for these gains to also translate into tactical and strategic impact on the business, a conscious investment in skills development, data quality and changed working methods is required. This aligns with insights from Al-Kfairy (2025), who emphasises that the long-term value of generative AI depends on its integration into the company's overall business objectives. According to Al-Kfairy, such integration requires cross-functional collaboration to ensure that AI solutions are not just technically robust but strategically aligned and embedded across the organisation.

This highlights an important factor in the adoption of generative AI where, while technology can accelerate operational tasks, its wider organisational value depends on how well it fits into existing structures. As Edwards et al. (2000) points out, the quality of decision-making is not determined solely by data availability, but by the ability to translate insights into action. Several respondents describe how initial enthusiasm waned when automation did not fully match the users' working methods or capabilities. This suggests that efficiency improvements alone are not enough, without organisational anchoring, the technology risks delivering specific improvements rather than broad transformation.

6.1.2 Prompting as a key to unlocking AI potential

It is explicit that generative AI offers great opportunities for automation and efficiency, but the interviews show that the technology places high demands on the user. It requires not only technical competences, but also the ability to understand how the model works and how to communicate with it. The respondents return to the importance of giving generative AI a clear structure to start from, and to ask well-formulated, contextually anchored questions.

It is distinguished that many users are still in a learning phase where they are testing their way around, and several express that the tool must be fed with both structure and expertise in order to deliver useful results. This confirms that generative AI does not yet function as an intuitive assistant, but rather as a powerful tool that demands active user interaction. Prompt design thus emerges as a new competence area, where technical ability, business understanding and communication skills must intersect. As interaction increasingly happens through natural language, the ability to ask the right question becomes just as important as writing code.

According to Drosos et al. (2024), this calls for a redefinition of what constitutes analytical competence in AI-driven environments. At a tactical level, this means the organisation must create opportunities for employees to develop such skills, for example through training, experimentation spaces and the sharing of effective prompt examples. To be effective, such initiatives should be integrated into existing workflows and tailored to different roles, allowing both technical and non-technical staff to build confidence and relevance in using generative AI. Encouraging collaborative learning across functions can also help surface best practices and support a shared understanding of what "good prompting" looks like in different contexts. On an operational level, prompt engineering directly impacts the quality of the AI output, which in turn shapes trust in the technology and influences how widely it will be adopted in daily analytical work.

6.1.3 Reimagining data interaction beyond dashboards

The interview findings show that there is a common perception in the organisation that analytics is mainly about dashboards. This mindset can limit the potential of more advanced analytical methods. Instead of relying on fixed visualisations, generative AI opens up the possibility for more flexible and intuitive ways to interact with data, such as asking questions in natural language and receiving relevant insights. This shift moves away from static tools toward a more dynamic and user-friendly experience. This aligns with Drosos et al. (2024), who argues that generative AI can support the entire analytics process by automating structure, visualisation and insight generation.

From a decision-making perspective, the interviews also highlight a clear distinction between operational and strategic decisions in terms of AI's usefulness. At the operational level, generative AI is seen as particularly valuable as it can be used to automate parts of the decision process, such as approvals or routine analysis, freeing up time and reducing manual workload. This view is consistent with Brink et al. (2024) and Magliocca et al. (2024), who state that operative decisions highly suitable for automation through generative AI. In contrast, when it comes to strategic decisions the picture becomes more complex. The theoretical framework suggests that uncertainty plays a key role in determining AI's usefulness. According to Brink et al. (2023), strategic decisions involve the highest levels of uncertainty, making them unsuitable for full automation. The interviews confirm that AI, in this context, serves mainly as a cognitive assistant rather than an autonomous decision maker. There is a clear awareness within the company of when generative AI can be used independently and when it cannot. This is considered essential for utilising generative AI to support effective and well-informed decision-making. Generative AI can contribute by summarising scenarios, offering decision support, or identifying patterns in large datasets, but the final decision still rests with humans.

6.1.4 Understanding the limits of generative AI

Although generative AI can automate and streamline several parts of the analysis process, it is clear from the interviews that the technology is not suitable in all contexts. A risk is identified that generative AI is being used in situations where simpler methods would be more effective. This is assumed to be especially true at an operational level, where certain tasks are sufficiently well-defined to be handled more quickly and precisely using traditional tools such as SQL or rule-based logic. It shows that the choice of technical tool should be adapted to the nature of the task rather than being driven by the novelty value of the technology. That is, always ensure that tools that are implemented and used are fit for purpose.

At a tactical level, there is a need to develop criteria for when generative AI should be used. This requires technical judgement and awareness of the tool's limitations. According to Magliocca et al. (2024), the usefulness of AI decreases when it is applied outside its natural scope. Misuse can create inefficiencies, overworked solutions and reduced trust. This is clearly noted by respondents who mention increased time spent on certain tasks when generative AI is integrated in the work. It is also considered crucial, from a strategic decision-making perspective, that generative AI is used in line with the organisation's goals and not as an end goal in itself. Generative AI is not a universal solution but should be considered as a complement to other tools. To achieve long-term benefit, the organisation must develop a strategy where generative AI is integrated with human judgement and business logic, as confirmed by Hyunh (2024) and Brink et al. (2023).

6.1.5 Why data structure determines success or failure

How the data is structured is crucial for the effectiveness of generative AI. At an operational level, existing data structures often work satisfactorily for standardised analysis and reporting. This enables rapid AI-supported answers to recurring questions, but at the same time limits more complex analysis. The structure of data is consistently noted by all respondents as one of the most crucial factors for successful integration of generative AI and it is currently a significant bottleneck.

At a tactical level, a lack of common definitions, business logic and master data becomes an obstacle. According to respondents, different parts of the organisation often use different interpretations and structures of data, which makes coordinated analysis difficult. This is in line with Wamba-Taguimdje et al. (2020), who argue that semantic ambiguity and fragmented data quality reduce the value of AI solutions. For generative AI to be used at scale, data governance, clear ownership and unified models are considered necessary.

Ericsson has made changes to how data responsibility is distributed across the organisation and, in connection with this, has identified a need to shift the culture around data usage and sharing. According to the respondents, there still appears to be a prevailing mindset of restricted access to data, which remains a challenge. In this context, change management, and more specifically Kotter's model, is seen as a relevant approach to fostering technological acceptance at the organisational level.

From a strategic perspective, the implications are even greater. Strategic decisions require integrated data sources, scenario-based analysis and cross-functional understanding. Without a common data foundation, generative AI risks reinforcing silos rather than breaking them down. Malacaria et al. (2023) emphasise that AI-readiness is not just about technical infrastructure but also about governance, metadata and semantic coherence. For generative AI to contribute to strategic development, more than technical tools are needed, it requires a structural mature data environment.

The lack of such maturity is considered to lead to a paradox where the more advanced the AI tool is, the more sensitive it becomes to a lack of data. The interviews describe how generative AI sometimes produces advanced analyses based on inadequate or fragmented data. This reinforces Wamba-Taguimdje et al. (2020), who point out semantic ambiguity as a key obstacle to the use of generative AI. At a strategic level, the risk is considered to be even greater. If different units interpret key metrics in different ways, AI-driven insights can mislead rather than support. This shows that shared data is not enough but shared meaning, grounded in both technical structure and business logic, is also of importance.

6.2 The organisational conditions for AI-supported analytics

While the technical possibilities appear tangible, the results show that the organisational context largely determines whether these possibilities are realised. For generative AI to contribute to efficiency, more than technical solutions are often required, it also requires changes in working methods, the distribution of skills and responsibilities.

6.2.1 Structural barriers in complex environments

A central theme from the interviews is that many of the challenges related to the integration of generative AI into the analytics workflow are not technical in nature, but organisational. While the AI technology itself is viewed as relatively mature and full of potential, several structural barriers slow down its practical implementation. This aligns with Wamba-Taguimdje et al. (2020), who argue that organisations must rethink how they operate in order to successfully implement generative AI in a way that creates real value.

One such barrier, frequently mentioned by the interviewees, is the size and complexity of the organisation. Respondents describe Ericsson as a “brownfield setup”, an environment with a legacy of fragmented systems, siloed data flows and outdated technologies that are still in use. With multiple business areas operating under different objectives, coordination becomes difficult. The challenge lies not only in aligning tools and platforms, but also in harmonising business logic, priorities and expectations. At a strategic level, this reflects the difficulty of establishing a common direction for data and AI and ensuring that different business units interpret and use data in a way that aligns with overarching goals. This highlights the need for cross-functional collaboration to drive long-term value, as emphasised by Al-Kfairy (2025), and reinforces that the difficulties are not only technical, but deeply rooted in how the organisation is structured and how it functions.

From a tactical point of view, several respondents stress that significant time is spent trying to align definitions and requirements, rather than performing actual analysis. One respondent explains that the challenge is not writing the SQL code, but agreeing on what should be measured. This indicates a lack of shared understanding and defined roles, which slows down the analytics process and creates delays in decision-making. These findings resonate with Johnson and Verdicchio’s (2024) sociotechnical perspective, which argues that technology alone cannot solve complex problems unless it is integrated with appropriate organisational processes and practices. A clear illustration of this is the uncertainty around data ownership and direction, who defines the scope and who has the authority to set standards. Such ambiguities disrupt tactical coordination, where alignment between IT and business functions is critical to transforming data into usable insights.

At the operational level, semantic misalignments and inconsistent interpretations of data directly impact the day-to-day use of analytics tools. Different parts of the organisation interpret data and its meaning in different ways, leading to inconsistent decisions and inefficiencies. There is a lack of common definitions for central concepts, which makes it difficult to scale technical solutions, especially AI-based systems that require uniform data models. The lack of common semantics means that different actors in practice work based on different understandings of the same data, which then forms the basis for different decisions. This clarifies the need for strengthened data governance, not only as a technical structure, but as an organisational framework that ensures that data is understood, owned and used in a uniform way across business boundaries. Such governance would not only reduce the risk of duplication of work and misinterpretations, but also enable more accurate data-driven decisions.

6.2.2 Access vs innovation

Another theme that emerged is the centralisation of data ownership and access, where only selected individuals have the mandate to work with certain datasets. While intended to maintain control and security, this model creates bottlenecks and often delays analysis to the point where business needs have already shifted. Internal processes are designed primarily for stability, which makes it difficult to experiment or act quickly on new ideas. For tactical and operational decisions, this cautious culture inhibits rapid iteration, experimentation and adaptation, all of which are critical for AI-based innovation. This culture reflects an organisational focus on risk minimisation rather than learning, something that according to Hiatt (2006) in the ADKAR model must be addressed for change to occur. To ensure that work on generative AI does not happen in a silo, ownership and responsibility for AI should be clarified at the business unit level. A structured change management approach could be implemented, inspired by models such as Kotter or ADKAR. This can include clear communication of goals, visibility of early successes, and tailored training for different roles, all to increase acceptance and reduce resistance.

Beyond the practical consequences, centralisation also shapes the organisation's overall approach to data. When access is restricted and responsibilities are siloed, it creates a mindset where data is seen as something to protect rather than something to share and collaborate around. This can lead to an exaggerated sense of sensitivity, where even low-risk data is treated as critical. Such attitudes discourage experimentation and create hesitation around using new tools like generative AI, which rely on broad access to varied datasets and the ability to iterate quickly.

6.2.3 Making data usable beyond operations

A more foundational insight concerns the data itself. Several interviewees point out that most of the organisation's data is structured to support operational decisions, not strategic analysis. While generative AI could enable more advanced insights, its usefulness is limited when the underlying data schema is designed for point-by-point reporting. This challenge reflects that data governance is not only about data quality and security, but also about making data semantically usable. This is a point emphasised by Khatri and Brown (2010), who argue that large organisations need consistent and shared definitions to effectively scale data-driven initiatives.

Lastly, the theoretical perspective of decision-making as a source of competitive advantage (Edwards et al., 2000) is considered relevant. Generative AI has the potential to support decisions across operational, tactical and strategic levels. However, when data structures are outdated, governance unclear and collaboration between business and IT limited, that potential remains untapped. Several respondents expressed that, in practice, many strategic decisions are still made based on intuition rather than insights, not because data or tools are missing, but because the organisational capacity to support data-driven decision-making is not yet in place. This, in turn, risks undermining the competitive edge that generative AI could offer.

6.3 The role of environmental aspects in AI-supported analytics

Despite the technical potential that generative AI offers, the interviews show that external environmental factors play a crucial role in how the technology is actually used within the organisation. The most prominent factor is the uncertainty surrounding regulatory requirements, both at a global and local level. Several respondents describe that it is not necessarily the formal rules that limit use, but also how these are perceived and interpreted within the organisation. A culture of caution has emerged, especially in the handling of data, where in some cases it is considered safer to refrain from using certain information or certain AI tools than to risk violating external or internal guidelines. This suggests that the organisation's interpretations of external requirements in practice shape the space in which innovation can occur.

As Tornatzky and Fleischer (1990) noted, laws and regulations can both hinder and stimulate innovation. The lack of clear regulatory guidelines for generative AI that Schneider et al. (2024) discusses, could create a vacuum in which organisations tend to act more restrictively than legally required, especially in globally operating companies where the complexity of compliance is high. Wamba-Taguimdje et al. (2020) emphasise that this type of institutional caution is not only a consequence of legal requirements, but also of internal interpretations and norms, which can slow down the operational impact of the technology.

Another aspect that several respondents return to is the need for security and regulatory compliance. It is not only technical errors that are perceived as threats, but also the risk of data manipulation or misuse. Malacaria et al. (2023) describe that AI governance in multinational companies requires special emphasis on both data security, access control and traceability, factors that, according to the interviews, clearly affect how generative AI may be used in practice.

At a strategic level, this becomes a dilemma between being at the forefront and minimising risk. According to several respondents, even data that is not particularly sensitive is sometimes treated as if it were business-critical, which points to a culture where caution is often given higher priority. At an operational level, this can mean that every application of AI must be reviewed, documented and approved in several stages, which risks slowing down the pace of development work and thus making it more difficult to work agilely with new tools.

The interviews also indicate that interest in generative AI is particularly strong at the moment, both within the organisation and externally. The technology is described as both new, exciting and promising, which creates a culture where many want to try it out in their own context, sometimes even without a clearly defined need. According to respondents, it is not uncommon for initiatives to be started based on a desire to be part of the development, rather than based on a concrete business case. This illustrates how external trends and the topicality of the technology affect internal priorities. At the same time, the responses show that this commitment is not necessarily seen as problematic, rather there is an awareness that generative AI has great potential, but that clearer structure and prioritisation are required for it to be of real benefit. This highlights the need to be thoughtful when implementing new technology and really look at the concrete value.

Ultimately, this raises questions about what kind of organisational capacity is needed to navigate a rapidly changing external environment. Currently, much of the responsibility appears to rest with legal and compliance functions, which according to respondents may create bottlenecks. A more distributed model for AI governance, where regulatory understanding is embedded across teams, could reduce dependency on centralised approvals.

6.4 Working with AI, not against it

Throughout all interviews, the importance of human influence in connection with the use of generative AI is highlighted. The empirical material clearly shows that AI's potential is only realised when the user knows how to control, understand and interpret it. Several respondents describe that they received useful help from generative AI in, for example, code generation or troubleshooting, but that it also required an active role on their part to evaluate the relevance and correctness of the answers. Tancredi (2024) highlights the importance of human oversight in data-driven decision-making processes, introducing the concept of the human-in-the-loop method. As illustrated in Figure 2, the higher the stakes of a decision, the greater the need for verification and human involvement. In the context of the specific organisation, a wide range of decisions are made, and while operational decisions may require less human intervention, strategic, high-stakes decisions are significantly more dependent on human participation.

In order to facilitate effective collaboration between humans and AI, Norman (2013) introduces Human–Computer Interaction (HCI) as a crucial perspective. While the human role remains central even in the implementation of new technologies, HCI becomes particularly important for ensuring that this involvement does not hinder efficiency. To fully realise the potential of generative AI and achieve the efficiency gains that the organisation is striving for, systems must be intuitive and aligned with how people work.

According to respondents in the study, users must ask questions to generative AI in a precise and informed way to get relevant answers, which require some understanding of data, models and their context, which is also reinforced by Drosos et al. (2024). This reflects a central theme in contemporary use of generative AI, that technical competency is no longer just about being able to program or interpret numbers, but about being able to interact with an AI in a goal-oriented way. In the empirical material the difficulty of formulating good prompts is identified as a bottleneck to achieving effective use of generative AI, which introduces the concept of prompt engineering as a new core competence in data analysis.

This shift has implications, changing both power and access to tools within the organisation. As analytics tools become more accessible through language interaction, opportunities are created for more people to participate in the analytics process. But at the same time, a new gap in competence is emerging, where some users have both the technical and contextual ability to interact with generative AI effectively, while others risk falling behind. As a result, the organisation must actively work to build new forms of data and AI expertise, not least in roles that were previously not considered technical.

7. Conclusions

This study set out to investigate how generative AI can be integrated into the analytics workflow within a large, globally operating organisation, focusing on two core questions: (1) What are the major challenges and enablers associated with an organisation's adoption of generative AI and its integration into the analytics workflow? and (2) In what ways can generative AI enhance efficiency within the analytics workflow, and how does it contribute to more effective decision-making?

7.1 Challenges and enablers for adoption and integration

The findings reveal that while generative AI holds strong potential, its successful adoption is shaped by several key enablers and challenges. Major enablers include organisational readiness, cross-functional collaboration and effective data governance. In particular, the shift from traditional data ownership to a more collaborative and strategically aligned data management model emerges as critical. This involves enabling access to relevant, high-quality data across domains while ensuring compliance and ethical standards.

Conversely, significant challenges include limited user competence, especially in prompt engineering and critical evaluation of AI outputs, as well as concerns around data quality, organisational silos, and regulatory constraints. Furthermore, cultural readiness plays a decisive role, a culture that encourages experimentation, learning, and innovation is essential for scaling generative AI beyond isolated use cases. Without this, the technology risks remaining underutilised or misaligned with business objectives.

7.2 Enhancing efficiency and supporting decision-making

Generative AI has demonstrated a clear capacity to streamline key elements of the analytics workflow, such as coding, data structuring, summarisation, and reporting. By automating these repetitive and time-consuming tasks, analysts are able to shift focus from operational tasks to more value-adding, strategic activities. This redistribution of effort not only improves efficiency but also enables deeper analytical thinking, more proactive insight generation, and greater contribution to long-term decision-making processes.

However, the strategic impact of generative AI remains limited unless supported by aligned data structures and a redefined decision-making framework. As AI begins to support, and in some cases generate, insights that feed into strategic decisions, organisations must clearly define the boundaries between automated and human-led decision-making. Human expertise remains essential for interpretation, ethical oversight, and the validation of AI-generated outputs.

Ultimately, the study concludes that the integration of generative AI into analytics is not merely a technical process but a socio-technical transformation. The full realisation of its benefits depends on both individual capabilities and organisational conditions. As such, organisations that invest not only in the technology itself but also in the necessary cultural, structural, and educational foundations are more likely to unlock the transformative potential of generative AI. This requires a long-term perspective which does not view generative AI as the definitive solution, but as a catalyst for how decisions are made and value is created across the organisation.

7.3 Future research

This study has shown that generative AI has great potential to influence how analytical work is carried out, but there are limitations in today's technical capabilities and organisational structure. The results raise several new questions that could not be answered within the framework of this study, but which are central to understanding the long-term significance of the technology.

A particularly important question raised by this study concerns the distribution of responsibility in organisations where generative AI is used as decision-support or decision-maker. As AI solutions become more advanced and begin to generate analysis and recommendations, uncertainty arises about who bears the actual responsibility for a decision. Future research should deepen the understanding about how responsibility and ownership for AI-generated decisions are distributed in practice and how this is affected by the nature of the decision.

It may also be relevant to examine further how this distribution affects trust in the technology, organisational transparency and the ability to act on insights. Especially in large or regulated organisations, there is a risk that unclear responsibilities lead to technology being used too cautiously. A future study could follow how roles develop over time in organisations where AI is integrated into core operations and how mandate and collaboration are shaped when people and technology share decision-making space.

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Appendix A – Interview guide

Current analytics workflow

1. Can you tell me about yourself and your role at Ericsson?
2. Where would you place yourself in the analytics workflow and how does your work contribute to the overall analytics process?
3. Can you describe the current decision-making process by giving an example? Earlier tasks/process.
4. What tools are used when handling data (Excel, SQL, Python, PowerBI)? And what tools?
5. Are all decisions made using data? In other words, does data play a role in all decision-making processes?
6. What factors do you believe are important for a decision to be considered a good one?

Identifying bottlenecks and challenges

7. What challenges do you face in your work, and can you give an example?
8. What challenges do you generally see arising within your analytics workflow?
9. Which part of your work is the most time-consuming?
10. Are there any organizational or cultural factors that influence how the process looks today, as well as how it may change in the future?

Potential for generative AI in analytics

11. Do you discuss the use of generative AI (its opportunities and risks) with your colleagues, and at Ericsson in general?
12. What is the general attitude toward AI?
13. Are there already any AI tools being used today to support your work in the process?
14. What features do you consider most important in the tools you or your team use?
15. What opportunities and challenges do you see for generative AI to improve your work?
16. And for generative AI to improve the overall analytics workflow in your organization?

17. What expectations and wishes would you have as a user for an AI system that supports your analytics workflow?

AI implementation and adoption challenges

18. What factors would influence your trust in AI-generated recommendations, such as transparency, explainability, and data sources?

19. Are there any concerns from employees or leadership about the transparency or reliability of AI-generated insights?

20. How do you see the role of AI in this context evolving in the future?

21. In what ways does your company's industry or regulatory environment shape the way AI is used?

22. In what ways do human analysts intervene or validate AI-generated insights before making business decisions?

23. How do you view prompt engineering as a crucial part of adoption?

24. Do you have any final thoughts or concerns?