Artificial Intelligence in Network Engineering and Consulting: Enhancing Efficiency and Custom Solutions

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Preface

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Abstract

This thesis researches the role of Artificial Intelligence in improving processes within network engineering and consultancy, especially focusing on efficiency, accuracy, customization, and the challenges of AI adoption. The research explores the main research question: *To what extent can AI assist network consultants and engineers in enhancing the efficiency and accuracy of engineering processes, particularly in the context of customized requirements?* To be able to answer this the research was divided by four sub-questions which explore the impact AI has on standard engineering tasks, its role in addressing customized requirements, the potential for time and cost savings, and the challenges associated with its integration.

With the use of a mixed-method approach, the study combines both quantitative data from structured interviews with qualitative insights obtained from semi-structured interviews. The results indicate that AI significantly enhances efficiency and accuracy in engineering tasks by automating processes such as network configuration and performance monitoring, thus minimizing errors and optimizing workflows. Predictive maintenance has become a significant benefit, enabling proactive issue resolution and minimizing operational downtime. However, the application of AI in customized tasks is limited by its dependence on resource-intensive processes and the need for domain-specific data, highlighting the importance of human expertise in addressing client-specific requirements.

The research establishes critical barriers to AI adoption, including technical challenges such as disconnected data systems and integrating difficulties, ethical concerns around job displacements and trust in AI systems, and regulatory compliance with frameworks such as EU AI Act and GDPR. Despite these challenges, the revolutionary potential of AI is clear, offering significant time and cost savings in standardized tasks and providing a supportive role in customization.

By highlighting the strengths and limitations of AI in network engineering, this study contributes to the academic understanding of this subject. The results provide practical insights for organizations aiming to effectively integrate AI into their operations, with recommendations focusing on enhancing AI's adaptability, improving data governance, and fostering human-AI collaboration. The study also identifies potential areas for future research, such as evolving roles of network engineers in AI-driven environment, experimental validation of AI benefits, and the development of adaptive AI models for customization.

By addressing these aspects this research highlights AI's dual function as a tool for efficiency in standard tasks and a complementary resource in customized solutions, paving the way for its responsible and innovative use in network engineering and consultancy. This study established a foundation for future progress, highlighting the need for ethical, technical, and regulatory considerations to ensure successful AI adaption.

Contents

Chapter 1

Introduction

This chapter provides an overview of the thesis topic, beginning with the company where the research is conducted, providing the necessary background context. Furthermore, it identifies the problem statement and formulates the research question. Following this, the chapter describes the selected research approach and emphasizes its importance within the scope of the study. Finally, it explains the relevance of the thesis and the potential contributions to the field.

1.1 Company Description

KPN, also known as Royal KPN N.V. is actives as a provider in the telecommunications and ICT industry. It's headquarters are based in Rotterdam, The Netherlands. KPN was in 1881 established. The company provides different services to both corporate and private clients. KPN offers different kind of services, including mobile and fixed-line telephony, high speed internet, and digital television. KPN also provides advanced ICT solutions such as cloud services, data centers, and cybersecurity for both consumers and businesses. The company prioritizes technological innovation, and invests technologies such as Internet of Things (IoT), 5G, and fiber optics. Aiming to improve its digital exclusivity and reduce its environmental footprint, KPN also prioritizes sustainability. These efforts strengthen KPN's standing as a key player in the telecommunications sector, with its dedication to providing reliable and innovative services (KPN, 2023, 2024).

In the context of this thesis, KPN plays an important role, as one of the largest telecommunications providers in The Netherlands. Especially in fields such as network design, optimization, and engineering, the firm has been at the front of digital transformation. As companies keep incorporating Artificial Intelligence (AI) driven technologies into its operations, and such KPN also incorporates it, it provides a valuable case for exploring the potential of AI to automate tasks that are traditionally performed by network engineers and consultants. Currently KPN is trying to integrate AI, such as HR Dot, the HR AI bot that KPN uses. This bot makes use of GenAI, and helps the employees with HR-related questions. As of the moment of writing the consultant and engineers in KPN don't make use the possibilities that AI has. Furthermore, in the experience stores that KPN has, clients are greeted by an AI hologram called Chaty, this hologram not only greets, but also helps the workers by communicating the client needs to them, making the experience more personal.

KPN also has a vast client database, which could provide valuable data for analyzing the practical applications of AI. As KPN collects data from its clients, this offers a unique opportunity to assess how AI can optimize both large-scale and individualized services, which could make the company's experience also directly applicable to the other large companies.

1.2 Problem Indication

The telecommunications sector is driven by an increasing demand for efficient, accurate, and flexible network solutions. Network engineers and consultants must design, implement , and maintain increasingly complex infrastructures which both satisfy bot standardized operational criteria and highly customized client requirements. On top of these challenges, the need to optimize costs and resources while still delivering high performance and reliability is growing.

AI has emerged as a transformative tool in an effort to resolve these challenges. AI applications, such as predictive maintenance, resource optimization, and traffic management, have shown considerable promise. AI-driven predictive maintenance addresses failures before they occur, reducing downtime and enhancing Quality of Service (QoS) (Vemuri et al., 2022). Similarly, machine learning techniques for anomaly detection and traffic prediction are driving dynamic and adaptive network configurations (Folorunsho et al., 2024). AI-driven optimization strategies also address the complexity in network configurations and routing protocols (Umoga et al., 2024).

1.3 Problem Statement

However, AI systems are limited in the context of highly customized network designs, as they depend on historical data and predefined parameters. Practical challenges such as prolonged design times, higher error rates, and limited collaboration between AI systems and human experts remain (Yadav et al., 2023). Balmer et al. (2020) stated that ethical and regulatory issues, such as data protection and transparency further complicate AI integration into workflows. AI has the potential to improve efficiency for standard tasks (Venkataram, 1997), its practical effects on time and costs savings, especially in customized engineering workflows are still investigated (Bajpai, 2023).

These problems highlight the necessity of extensive studies for the role of AI in supporting both standard and customized engineering tasks. This includes assessing its potential to enhance efficiency, accuracy, and collaboration, as well as addressing potential technical limitations and ethical challenges.

1.4 Research Question

Based on the problem statement the following research question has been developed:

To what extend can Artificial Intelligence (AI) assist network consultants and network engineers in improving the efficiency and accuracy of design and engineering processes in the context of customized requirements?

With the research question in mind, the following sub-questions have been formulated:

1. How can AI improve the efficiency, accuracy, and collaboration in standard engineering tasks for network consultants and engineers?

   This sub-question is about how AI fits within normal engineering processes and focuses on global concepts such as automation, productivity, and collaboration between AI and humans. It concentrates on tasks that are predictable and can be efficiently accessed within a short time frame. By examining the potential of AI to enhance routine operations, this question contributes to the overarching research objective of assessing how AI can improve the efficiency of engineers and consultants.

2. To what extent can AI tools support engineers in addressing customized design requirements, and what limitations do they face in this area?

   The second sub-question investigates AI's effectiveness in managing customization, considering both its strengths and limitations. It focuses on customized requirements, which are generally more intricate than standard tasks. By exploring how AI balances its support and constraints in these scenarios, this question provides insights into AI's capability to handle non-standard, client-specific designs.

3. What are the potential time and cost savings from AI implementation in engineering design, both for standard tasks and customized requirements?

   The third sub-question explores the practical impact of AI on engineering workflows by focusing on quantifiable benefits, such as time and cost savings. It examines both standard and customized tasks to assess the tangible value AI provides in engineering processes. By addressing the economic and operational effects of AI integration, this question aligns with the broader research aim of evaluating AI's overall contribution to network consulting and engineering.

4. What challenges, including ethical and regulatory concerns, do network engineers and consultants face when integrating AI into their workflows?

   The last question relates to the technical, ethical, and regulatory aspects of AI adoption. It gives a broader perspective on AI implementation landscape through the lenses of challenges faced by engineers in integrating AI tools. This question contributes to the overarching research question by determining what aspects of AI might have difficulties being fully realized and balance the discussion of both benefits and downsides of AI.

1.5 Research Design

This thesis employs a mixed-method research design and helps to determine how much AI can help network engineers and consultants in making more effective and precise design and engineering processes while also catering to standardized and customized requirements. Mixed-method designs combine both quantitative and qualitative approaches, offering the best of both worlds by combing both both data that is measurable and insights from experiences of experts (Creswell, 1999).

The quantitative data was collected through a survey distributed to 30 mainly network engineers and consultants, but also people who work with either AI or networks. This survey collected their perceptions of the impact AI has on efficiency, accuracy, and customization in network engineering tasks. The survey included 25 close-ended questions, making use of a 5-point Likert scale to measure their attitudes and experiences in a systematic way.

The qualitative data was collected through 12 semi-structured interviews, these interviews were conducted with industry professionals such as network engineers, network consultants, managers of network engineers and/or consultants, an automation manager, a process manager, and a cybersecurity specialist. This approach has allowed for an in-depth exploration of challenges and opportunities that AI presents in addressing highly customized requirements. The combination of statistical and thematic coding provided a deep understanding of AI's potential in improving network design processes while also shedding light to adoption barriers.

1.6 Contribution

This thesis contributes to the existing body of knowledge on the application of AI in network engineering and consultancy.

It enhances the theoretical understanding of AI's role in improving operational processes within network engineering and consultancy. This research explores how AI improves efficiency and accuracy in standard engineering tasks, addresses challenges in supporting customization, and provides insights into the technical, ethical, and regulatory challenges which influence AI adoption. It focuses on the telecommunications sector within the Netherlands, providing localized insights which bridge the gap between general AI literature and its application in specific contexts. The mixed-methods approach, combining quantitative and qualitative analyses, offers a methodological framework for future studies focused on the integration of AI in other sectors.

This research is relevant to organizations in the telecommunications and network engineering sectors, providing practical insights on the integration of AI to enhance operational workflows. The thesis provides practical advise for organizations wanting to increase performance by highlighting AI's ability to optimize operations, enhance customization, and achieve cost and time savings. Furthermore, it highlights techniques for navigating regulatory frameworks such as the EU AI pact, ensuring compliance and ethical practices. These findings highlight how organizations might utilize AI to gain a competitive advantage in a increasingly dynamic and technology-driven industry.

1.7 Structure of Thesis

The structure of the thesis consist of a few chapters. The chapters are divided as following, chapter 2 consists of the literature review, the literature review will explore previous studies in order to identify various gaps which are related to the core concepts. Chapter 3 will be based on the methodology, in the methodology the thesis background will be covered and the methods used for data collection and analysis will be explained, this offers a detailed insight into the process of the thesis research. Chapter 4 will present the results, the results will be shown in an extensive summary, and the findings of the data analysis will be presented here. In chapter 5 the results will be discussed, this will be done via interpreting the results and thus giving the results a meaning. In chapter 6 a conclusion will be made, here the research question will be answered, limitations will be explored and recommendations for possible future research is offered.

Chapter 2

Literature Review

This chapter explores the research on AI and its application on network engineering and consultancy. It delves into how AI could improve the efficiency, accuracy, and collaboration in standard engineering tasks for network engineers and consultants. It furthermore examines to what extent AI tools could support engineers in addressing customized design requirements, and what limitations they face in this area. Moreover, the potential time and cost savings from AI implementation in engineering design, for both standard tasks and customized requirements will be explored. At last the challenges, including ethical and regulatory concerns, that network engineers and consultants face when integrating AI into their workflows will be explored. By reviewing what has already been studied, this chapter will identify the gaps in current knowledge. This will help with set the foundation for the research design.

2.1 Theoretical Framework

2.1.1 Artificial Intelligence

AI is a groundbreaking technology that is gaining popularity in many industries as it is transforming the way we conduct tasks or make decisions. The concept of AI can be traced back to 1950 , Alan Turing suggested that if it was possible for a computer to have a conversation with a human and it was not possible for a human to tell whether they were talking to another person or a machine, then the machine could be considered to have Artificial Intelligence. AI could be defined as the ability of a machine to perform functions related to human intelligence (in particular in relation to computer systems) (European Commission, 2024). These processes include learning (the acquisition of information and rules for its use), reasoning (using rules to reach conclusions), and self-correction (improvement in performance over time through feedback) (Chen et al., 2021). AI is an interdisciplinary field, borrowing concepts and methodologies from computer science, mathematics, cognitive psychology, and neuroscience (Nilsson, 1998).

AI refers to the simulation of human intelligence processes by machines, especially computer systems. These processes include learning, reasoning, and self-correction. Key components of AI include different subfield, such as machine learning (ML), deep learning and natural language processing (NLP) (Venkataram, 1997).

AI can be broadly categorized in the following: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). ANI, is also known as weak AI has already achieved a lot of success and its applied in different industries such as healthcare, finance, and technology (Girasa, 2020). AGI, also referred to as strong AI, is still a challenging and mainly theoretical area of research. Regardless of the enthusiastic goals, progress in AGI has been slow in comparison to the quick advancements and partial applications of ANI systems (Eberding, 2020; Grace et al., 2024; Welsh, 2019). This difference occurs because it is possible for ANI to succeed in specific, well-defined domains, while replicating human intelligence across different tasks stays a significant technical difficulty.

AI has different roles in different sectors. AI systems are engineered to analyze extensive datasets, perform complex calculations, and make decisions with exceptional speed and precision, making them essential in modern engineering tasks. In network engineering, AI applications include automating routine tasks and optimizing network performance to enhance cybersecurity measures, and facilitation of real-time data analysis. Research shows that AI-driven technologies enhance productivity and collaboration, which allows network engineers to address challenges such as managing complex systems and responding to emerging threats (Eberding, 2020; Grace et al., 2024). These capabilities highlight the transformative potential of AI in improving efficiency, precision, and innovation in network engineering (Alpaydin, 2020; Sheikh et al., 2023). As a result these technologies are gradually applied to network engineering processes, primarily to automate repetitive tasks, facilitate workflows, and enhance decision-making precision (Nguyen-Duc et al., 2023). AI has facilitated better network performance and customer service, , illustrating the role of AI as a catalyst of efficiency and innovation within the network engineering domain (Balmer et al., 2020).

Although such advancements have been made, AI implementation in network engineering and consulting is not without its issues. Data privacy, algorithmic biases, as well as the transparency of AI models are ethical and regulatory considerations which serve to present significant hurdles (Zhang et al., 2021). Furthermore, although much of AI is used to automate repetitive tasks, it has limited capacity in managing customized, specific client needs (Salehi & Burgueño, 2018). In an effort to overcome these limitations, the purpose of this literature review is to examine ways in which AI can be effectively leveraged to assist with standardized and personalized network design tasks.

Applications of AI in Networking and Network Engineering

Within network engineering, AI has helped it transform by providing advanced solutions which will help enhancing operational efficiency, security, and decision-making accuracy.

1. Network Management and Optimization

   AI tools are used to monitor and manage network performance in real-time. ML algorithms analyze traffic patterns to predict and prevent problems, optimize resource allocation, and ensuring seamless operations. Luntovskyy (2024) explored these advancements in depth, emphasizing the potential of AI in supporting advanced network technologies and future digital ecosystems.

2. Automated Network Configuration

   AI enables the automated configuration of network devices, which reduces the need for manual intervention and also minimizing human error. Tools such as Ansible and NAPALM utilize AI to implement consistent configurations across networks (Yadav et al., 2023).

3. Network Security

   AI enhances network security by detecting and mitigating cyberthreats in real-time. ML models can identify unusual patterns suggestive of security breaches and respond proactively to protect the network. This is also shown in the research by Venkataram (1997), it outlines the complexities and solutions in the modern day networks.

4. Predictive Maintenance

   It is possible for AI to predict equipment failures based on the historical data and performance parameters, allowing network engineers to address potential problems before they could lead to downtime, thus improving network reliability (Yadav et al., 2023).

5. Quality of Service (QoS)

   AI optimizes QoS by prioritizing network traffic based on the type of data that is transmitted. This ensures that essential applications receive the necessary bandwidth, improving user experience. Luntovskyy (2024)highlights the importance of QoS optimization in AI-driven digital ecosystems.

6. Intelligent Traffic Management

   AI analyzes network traffic to manage congestion effectively, By understanding traffic patterns, AI redirects traffic to less congested paths, distributing loads evenly, and reduces latency. Research provides insight into how AI can be utilized for intelligent traffic management in complex networks (Venkataram, 1997).

7. Fault Detection and Troubleshooting

   AI systems detect network faults and pinpoint root causes automatically, resulting in reduced time and effort required for troubleshooting. AI-driven diagnostic tools provide actionable insights for quicker resolution (Yadav et al., 2023).

8. Enhanced Customer Experience

   AI-driven chatbots and virtual assistants provide real-time support, resolving network-related queries and issues quickly, thus enhancing customer satisfaction. The potential of AI to improve customer experience in network services has also been researched by Luntovskyy (2024).

9. Data-Driven Decision Making

   AI processes extensive amounts of network data to provide insights on performance, user behavior, and potential improvements, facilitating strategic planning and network development. This data-driven approach has also been emphasized by Venkataram (1997) as important for modern network management.

The integration of AI into network engineering has the potential to significantly improve the efficiency and precision of design and engineering processes. AI tools can automate some day-to-day tasks such as network configuration and monitoring, which overwhelms them and gives them time to focus on more complex issues (Balmer et al., 2020). AI-driven predictive analytics can predict network failures and maximize performance while machine learning algorithms support adaptive network management to insure the network provides an environment that can withstand dynamically changing demand (Muller et al., 1993).

2.1.2 The role of Artificial Intelligence in Enhancing Efficiency, Accuracy, and Collaboration

Enhancing Efficiency

AI can significantly enhance the efficiency of network engineering/ network engineers by automating different aspects of network management. Regarding automated network configuration, AI-driven tools automate the configuration of network devices, this reduces the need for human interventions. This automation ensures that the configurations are consistent across the network, which minimizes human error and ensures compliance with organizational policies. Automated tools such as Ansible and NAPALM enable network engineers to focus on more strategic tasks, which improves overall productivity (Yadav et al., 2023).

When talking about real-time adaption and optimization. AI algorithms can adapt to changing network conditions in real-time, optimizing resource allocation and network performance. For example, it possible for AI to dynamically adjust bandwidth allocation based on the current traffic patterns, this ensures efficient use of network resources and reduces congestion. This real-time optimization leads to smoother network operations and better user experiences (Cui et al., 2024).

According to Venkataram (1997) it is possible to use machine learning models to analyze vast amounts of data, thus also network data, to also identify patterns and predict potential issues before they occur. This means that AI can optimize network operations by automating routine tasks such as monitoring, fault detection, and performance analysis. This proactive approach helps reducing downtown and eventually also improves the reliability of network services.

AI enhances efficiency through intelligent resource allocation, this is done by analyzing usage patterns and predicting future demand, AI systems can allocate resources where they are needed, this ensures that the network performs optimal. This allocation does not only improve efficiency but it also maximized the utilization of the resources available (Du et al., 2024).

It is also possible to have predictive maintenance powered by AI this would help in anticipating equipment failures before it is even possible for them to occur. This would be done by analyzing historical data and current performance metrics, AI can then predict when maintenance is needed, thus allowing network engineers to address potential issues proactively. This results in reduced unplanned downtime and enhances network reliability (Yadav et al., 2023).

Improving Accuracy

AI can enhance accuracy in network engineering through various advanced data analysis and anomaly detection. AI-powered tools can analyze vast amounts of network data to identify patterns and detect possible issues before they could emerge. Machine learning models can process and analyze this data in real-time, providing network engineers with accurate data into network performance and potential problems. This proactive approach allows for timely resolutions for issues, thus resulting in more reliable and stable network performance (Yadav et al., 2023).

It's possible for AI to enhance accuracy by detecting possible anomalies in network traffic that could indicate potential issues or security breaches. Machine learning algorithms could identify unusual patterns of behavior and take proactive measures to address them. This possibility is important for maintaining network security and ensuring the integrity of network systems (Folorunsho et al., 2024).

It is possible for AI to help with proactive troubleshooting, it could detect anomalies up to 60% faster than traditional monitoring methods, this enables proactive intervention before problems could escalate. This proactive troubleshooting will help reduce downtime and improves the overall reliability of network services (Venkataram, 1997).

According to Yadav et al. (2023) AI can reduce human error in network management with the help of automating routine tasks such as configuration, monitoring, and troubleshooting. Automated systems then can respond to network events in seconds, compared to the minutes or hours that it could have taken a human. This reduces the risk of errors and ensures consistent and accurate network operations.

Folorunsho et al. (2024) has also stated that AI systems can continuously learn from new data, this will help improve their accuracy over time. This is done by analyzing historical data and current performance metrics, AI can then refine its algorithms and provide more precise predictions and recommendations. This continuous learning process enhances the accuracy and reliability of network engineering tasks.

Facilitating Collaboration

With the help of AI collaboration can be enhanced among network engineers and network consultants, this can be done by providing real-time insights, optimizing communication, and enabling data-driven decision-making. Platforms that are powered by AI provide real-time insights into network performance, issues, and trends. These insights enable network engineers and consultants to make informed decisions quickly and efficiently. This could be done because they have access to up-to-date information, teams could collaborate more effectively and address issues as they arise (Balaram & Prabhu, 2023; Luntovskyy, 2024).

Cui et al. (2024) stated that with AI tools could facilitate optimized communication by integrating different communication channels and providing a centralized platform for sharing information. Collaboration tools such as Slack, Microsoft Teams and other platforms enable teams to communicate seamlessly, share updates, and coordinate tasks. This integration thus reduces misunderstandings and ensures that everyone is on the same page, this leads to a more effective collaboration.

AI can help collaboration by enabling data-driven decision-making. AI algorithms can analyze big amounts of data and provide insights that are actionable, this will help teams with making informed decisions that are based on accurate and relevant information. This data-driven approach reduces the risk of errors and ensures that decisions are backed by evidence, improving the quality of collaborative efforts (Yadav et al., 2023).

Yadav et al. (2023) has also stated that it us possible for AI tools to help in coordinating and managing tasks by providing automated workflows and project management features. With the help of these tools tasks can be assigned, progress tracked, and reminders send, this ensures that all team members are aware of their responsibilities and deadlines. This level of coordination ensures that teamwork will be done right and that projects are completed on time.

AI can help facilitate collaboration by the help of enabling problem-solving capabilities. AI-powered diagnostic tools can identify and analyze issues, providing teams with detailed reports and recommendations. This collaborative problem-solving approach makes sure that all team members can contribute their expertise and work together to resolve issues efficiently (Folorunsho et al., 2024).

Predictive Maintenance

Predictive maintenance in network engineering can be enhanced with AI, this is done by analyzing data to predict equipment failures before they will occur. Data from various sensors and network components can be analyzed with AI powered tools, these tools can also help predict potential failures. This can be done by leveraging machine learning algorithms, these tools then can help detect anomalies and provide early warnings, this allows network engineers to address issues proactively (Wiese, 2024; Yadav et al., 2023).

With predictive maintenance downtime can be reduced by scheduling maintenance tasks based on the actual equipment conditions rather than fixed schedules. This approach ensures that maintenance is only performed when necessary, which minimizes disruptions and improves network reliability (Wiese, 2024).

AI optimizes maintenance schedules by analyzing historical data and real-time performance metrics. This helps network engineers to plan maintenance activities more efficiently, thus reducing operational costs and extending the lifespan of network equipment (Wiese, 2024).

With predicting equipment failures before they occur, AI-driven predictive maintenance enhances the overall reliability of network systems. This proactive approach ensures that potential issues are addressed quickly, thus reducing the risk of unexpected failures and service disruptions (Wiese, 2024).

Various telecommunications companies have successfully implemented AI-based predictive maintenance systems. For example AT&T uses AI and machine learning to predict network failures by analyzing data from cell towers and fiber optic cables (Teletimes International, 2024). This proactive approach improves service reliability and customer satisfaction (Yadav et al., 2023).

Optimizing Quality of Service

QoS is used to manage network traffic and ensures the performance of critical applications within limited network capacity. QoS begins with identifying and categorizing different types of network traffic based on their requirements and importance. This classification helps in prioritizing critical applications (Zhao et al., 2024). Once the traffic has been classified, QoS assigns higher priority to critical traffic to ensure it receives guaranteed bandwidth and timely delivery. This prioritization helps in maintaining the performance of essential applications even during network congestion (Zhao et al., 2024).

QoS also reserves network resources such as bandwidth and buffer space for higher priority traffic to avoid competition and potential congestion. This will ensure that critical applications have the necessary resources for optimal performance (Zhao et al., 2024).

Mechanisms such as queuing and shaping to manage traffic flow during peak periods and prevents network overload can be implemented with QoS. This further helps in maintaining a smooth and reliable network experience (Zhao et al., 2024).

A few benefits of using QoS in network engineering are improved application performance, enhanced user experience, efficient resource utilization, and enhanced network security.

It is widely used in different scenarios, such as enterprise networks, service provider networks, data centers, and real-time applications (Caesar, 2024).

Enhancing Security

AI helps network security by identifying and mitigating cyberthreats in real-time. It enhances security by continuously monitoring network traffic for unusual patterns and potential threats. Machine learning models can then detect anomalies which may indicate malicious activity. This real-time threat detection enables network engineers to respond promptly and mitigate risks before they escalate (Kumar, 2024).

Security systems that are driven by AI can automate incident response by identifying threats and taking appropriate actions to neutralize them (Nnamani, 2024). AI are able to scan network devices and applications for vulnerabilities, prioritizing them based on their potential vulnerabilities, AI helps ensure that the most critical issues are addressed first, thus reducing the overall risk to the network (Komaragiri & Edward, 2022).

AI enhances security through behavioral analysis, this involves monitoring user and device behavior to detect deviations from normal patterns (Olabanji et al., 2024).

Security measures based on the evolving threat landscape can be adapted with AI. Machine learning models can learn from past incidents and continuously update their algorithms to detect new types op attacks. This adaptability ensures that the network remains protected against new threats (Kumar, 2024).

It is also possible for AI to seamlessly integrate with existing security infrastructure, enhancing the overall effectiveness of security measures.

AI is a transformative force in network engineering, driving improvements in efficiency, accuracy, and collaboration. By automating routine tasks, helping enable real-time optimization, and predicting maintenance needs, AI significantly boosts productivity and ensures the reliability of network systems. Its ability to analyze big amounts of data and detect anomalies empowers proactive problem resolution, improving accuracy and reducing human error. In addition, it facilitates seamless collaboration through real-time insights, optimized communication, and data-driven decision making, fostering more effective teamwork. Collectively, these advances highlight the important role AI has in shaping the future of network engineering, enabling networks that are more robust, efficient, and aligned with the demands of a dynamic technological landscape.

2.1.3 Artificial Intelligence's Support for Customized Design Requirements

AI has helped transform the field network engineering and consulting by enabling personalized and tailored solutions that were previously unimaginable.

Key Technologies

When speaking about network engineering and consulting, the application of AI has helped advance the capability to deliver customized design solutions. The primary technologies driving the transformation are Generative Adversarial Networks (GANs), NLP, and Computer Vision.

Goodfellow et al. (2014) has introduced GANs, it represents an influential development in the field of AI. These networks consists of two neural networks, the generator and the discriminator, these operate in tandem within a framework. The generator creates data instances, while the discriminator evaluates them. This process continues until the generator produces sophisticated network configurations that meet specific user requirements, thus enhancing the customization process. When in the context of network engineering, GANs can generate sophisticated network configurations which meet the specific user requirements, thereby enhancing the customization process. The effectiveness of GANs in producing high-quality, diverse outputs makes them particularly valuable in scenarios requiring custom-made network solutions.

NLP is a field of AI which focuses on the interaction between computers and human language. NLP enables systems to process and understand natural language inputs, facilitating more human-computer interactions (Brown et al., 2020). In network engineering, NLP can be used to interpret detailed design requirements expressed in natural language by stakeholders. This allows AI systems to translate complex user specifications into concrete network design parameters, and also optimizing the design process and ensuring alignment with user expectation.

The use of AI to interpret and make decision based on visual data is involved in Computer Vision. According to Krizhevsky et al. (2017) this technology has proven useful in different domains requiring precise visual analysis. Regarding network engineering, Computer Vision can be applied to visualize network layouts, identify potential issues in real-time, and enhance already existing network design based on visual feedback. This can be done by integrating visual data into the design process, Computer Vision ensures more accurate and more efficient customization of network infrastructures.

Applications

With the application of AI technologies the way of working has transformed, this is also applicable for customized design for network engineers and consultants, this way network infrastructures are planned, developed, and managed.

Tools powered by AI enable network engineers to create personalized network configurations and optimize existing networks. This is done by analyzing user requirements, network traffic patterns, and performance metrics, it's possible for AI to generate customized network designs specifically catered to individual needs. AI algorithms are able to optimize the placements of network nodes and the routing of data in order to enhance the efficiency and reduce latency (Cisco, 2024). These tools can furthermore simulate different network scenarios in order to identify the best configurations and predict potential bottlenecks before they deploy.

AI applications in network security provide network consultants with tailored security solutions. The security measures, threat models, and compliance standards are put in by users, after this the AI can generate customized security policies and configurations. As example, machine learning models are able to identify unusual network activities that may indicate security breaches, this allows for real-time threat detection and response (Bhattacharyya & Kalita, 2014). It is also possible for AI to help in designing robust security architectures by predicting potential vulnerabilities and recommending appropriate countermeasures.

Automating routine troubleshooting and maintenance tasks with AI-driven tools, allows network engineers and consultants on more complex issues. With continuous monitoring network performance and user behavior, it is possible to proactively identify and resolve issues with AI before they impact end users (Cisco, 2024). AI-powered predictive maintenance can forecast when network components are likely to fail and schedule maintenance accordingly, and also for the customized designs reducing downtime and improving network reliability.

Capacity planning can be enhanced with AI by analyzing historical data and predicting future usage patterns. Optimizing resource allocation ensures that network can handle peak loads without compromising performance (Cisco, 2024). Customized capacity planning which is generated by AI can help the network engineers and consultants avoid over-provisioning and under-provisioning, this leads to cost savings and efficient network utilization.

With the support of AI with QoS management, it can prioritize critical network traffic and ensuring optimal performance for essential applications. With analyzing real-time traffic data, it is possible for AI to dynamically adjust network parameters to maintain desired QoS levels (Folorunsho et al., 2024). This capability is valuable in environments where high-quality, uninterrupted service is crucial.

Potential Limitations

The implementation of AI in network engineering and consulting brings a few challenges and limitations which must be carefully considered to ensure the successful deployment and operation of network infrastructures. The limitations primarily revolve around data challenges, generalizability, computational complexity, and scalability. The potential challenges and limitations regarding technical, ethical and regulatory challenges will be further explained in section 2.1.5.

High-quality data is crucial for AI systems to generate effective customized networks. Nonetheless, collecting accurate and comprehensive information customized to specific requirements often presents a significant obstacle. Legacy systems often lack the requisite precision for advanced AI algorithms, and missing or inconsistent data may result in inadequate results. In addition, real-time data, vital to dynamic customization, may be subject to hardware limitations or restricted by organizational policies (C. Huang et al., 2023).

AI models often perform well in standard tasks but struggle with distinctive, highly customized requirements. Network designs customized to specific client needs may incorporate restrictions, objectives, or environmental aspects absent during training. Addressing these requirements necessitates retraining or fine-tuning AI models with domain-specific data, a process that can be resource-intensive and time-consuming (Van Stein et al., 2023).

Customized network designs frequently require balancing multiple, sometimes conflicting objectives, such as performance, cost, and energy efficiency. Customized network designs sometimes require a compromise of many, occasionally contradictory objectives, including performance, affordability, and energy efficiency. Although AI excels in optimization, multi-objective problems in customized settings can lead to significant computational and algorithmic complexity. Achieving optimal solutions in such situations might require specialized algorithms, extensive computational resources, and iterative validation, thus raising the operational load (Kulkarni et al., 2021).

The computational requirements for generating customized networks continue to be significant challenge. Simulating and optimizing complex networks for customized configurations sometimes calls for high-performance computing power, which may not be readily available to smaller firms or individual consultants. Although developments such as as model pruning and quantization, resource limitations may still limit the broad application of AI in customization (Gomez-Carmona et al., 2022).

Increasing AI-driven customization to meet the requirements of large networks presents further challenges. Although many AI systems work efficiently for small-scale or moderately complex customisations, their application to enterprise-level networks featuring complex connections and large information quantities sometimes results in decreased efficiency. Ensuring scalability while preserving the quality of customization is an essential area for improvements (Ismanov et al., 2024).

2.1.4 Potential Time and Cost Savings From AI Implementation

The integration of AI in engineering design can yield significant time and cost efficiencies, especially within network engineering and consultancy. AI minimizes manual labor, enhances procedures, and facilitates more effective resource allocation by automating repetitive operations and improving intricate workflows. This subsection analyzes these advantages by assessing their influence on both standardized and customized jobs.

Time Savings in Standardized Tasks

Routine network engineering tasks are significantly accelerated by AI-driven tools. Network configuration, performance monitoring, and problem detection can be executed in a much shorter time frame compared to traditional methods, AI-driven technologies such as Ansible and NAPALM automate network setups, guaranteeing consistency and minimizing the possibility of errors as much as 50%. This not only reduces setup time but also prevents delays resulting from troubleshooting configuration problems (Yadav et al., 2023). Predictive maintenance is an area in which AI generates significant time efficiencies. Through the analysis of past data and performance variables, AI systems can predict failures of equipment, allowing network engineers to prevent potential issues. This proactive strategy reduces downtime and facilitates more efficient network operations, thus decreasing the amount of time allocated to reactive troubleshooting (Wiese, 2024).

Quantifiable metrics from AI developments show reductions in computational requirements and processing times. AI technologies have shown the ability to reduce computational time for extensive tasks using efficient algorithms, such as a 44-time reduction in compute required to train models over a 7-year period (Hernandez & Brown, 2020). Similarly, methods such as model cascade techniques in AI applications can reduce computing time by more than 60% while maintaining accuracy (Gomez-Carmona et al., 2022).

Cost Savings in Standardized Tasks

AI significantly lowers labor costs and operational expenses by automating routine tasks. Predictive analytics and real-time resource optimization guarantee an efficient use of bandwidth and computational resources, preventing over-provisioning and under-utilization (Du et al., 2024). Furthermore, methods such as pruning and quantization of AI models have shown the capability of lowering operational expenses by compressing vast neural networks by as much as 75.8%, while sustaining minimal decreases in performance (Kulkarni et al., 2021).

The ability of AI to work as an alternative for expensive computational tasks significantly reduces costs. AI-assisted optimization pipelines are capable of replacing expensive real-world engineering calculations with proxy functions, thus reducing both the financial and time assets needed for complex problem-solving (Van Stein et al., 2023).

Time Savings in Customized Tasks

Tools powered by AI significantly reduce the time required to provide customized network solutions. Through the analysis of unique customer needs, traffic patterns, and performance objectives, AI systems can produce efficient configurations customized to specific needs. Diffusion model-based frameworks can quickly generate customized designs while complying with complex limitations, which decreases delivery times compared to traditional approaches (C. Huang et al., 2023).

In addition, real-time data integration and predictive modeling allow AI to modify designs dynamically in response to changing network conditions. This adaptability enables network engineers to reduce the time spent on manual adjustments and troubleshooting during implementation (Gomez-Carmona et al., 2022).

Cost Savings in Customized Tasks

AI-driven techniques additionally result in significant cost reductions in customized network design. Traditional approaches frequently involve iterative processes, leading to increased labor hours and raised operational costs. AI tools enhance these workflows, offering economical solutions through the utilization of predictive analytics and optimization algorithms (Ismanov et al., 2024).

Furthermore, AI reduces resource wasting by dynamically allocating bandwidth, computational power, and other network resources according to real-time demands. This accuracy guarantees optimal resource utilization, minimizing expenses related to over-provisioning or under-utilization(Du et al., 2024).

2.1.5 Challenges in Artificial Intelligence Integration

The integration of AI into network engineering and consulting processes offers numerous benefits, however it is not without its challenges. these challenges span from technical, ethical, and regulatory aspects, each of these poses barriers to the smooth adoption and implementation of AI tools. Addressing these issues essential to optimizing the advantages of AI while mitigating potential downsides.

Technical Challenges

A major technological advances challenges faced by network engineers and consultants is the quality and accessibility of data. AI systems depend heavily on vast amounts of high-quality, well-organized data to function well. However, network environments frequently generate heterogeneous and incomplete datasets, potentially undermining the accuracy and reliability of AI-driven technologies. Ensuring data consistency, cleaning, and preprocessing requires additional resources and particular expertise (C. Huang et al., 2023). Moreover, maintaining seamless interaction between AI-driven tools and human operators presents a technical challenge, especially in the context of real-time decision-making within dynamic network settings (Oduri, 2019).

The difference in skills among network engineers and consultants increases integration difficulties. Setting up and managing AI systems requires specific expertise in domains such as machine learning, data science, and AI software engineering. A substantial proportion of professionals in this field lack this experience, leading in a significant learning curve and requiring major investment in training and upskilling efforts (Gomez-Carmona et al., 2022).

Reliability and maintenance are additional factors. AI tools, despite their sophistication, are not perfect. They might find it difficult to adjust to unexpected situations, leading to network interruptions or incorrect outcomes. Continuous monitoring, debugging, and updating are essential for maintaining system stability, which could raise operational burdens (Van Stein et al., 2023).

Ethical Challenges

The integration of AI into network engineering processes additionally presents various ethical challenges. Bias and fairness are significant issues, as AI models trained on biased datasets could perpetuate or amplify existing biases in decision-making. This represents significant risks in domains such as resource allocation and network prioritizing, where fairness is important. Identifying and addressing bias in AI systems requires deliberate and proactive efforts (Ismanov et al., 2024). Another ethical challenges is the potential displacement of employees. As AI automates repetitive tasks, the role of human engineers in these processes may decline. This presents opportunities for engineers to focus on strategic activities, although it creates uncertainty about long-term employment prospects in heavily automated processes (Kulkarni et al., 2021).

Data privacy presents an important ethical issue, as AI systems often requires broad access to sensitive user information for training and functionality. This data, if not handled properly, poses privacy issues such as unauthorized access and misuse. These risks must be addressed through robust data governance and security measures to maintain trust in AI-driven systems (Oduri, 2019).

Regulatory and Compliance Challenges

Integration of AI needs to conform to various regulations and legal requirements. These regulations may relate to data protection, cybersecurity, and ethical use of AI. Navigating the complex regulatory framework can be difficult, especially as regulations evolve to align with advancements in technology. Failure to comply may lead to legal consequences and damage to an organization's reputation. It is imperative that AI systems comply with regulatory guidelines for their successful implementation. The European Union's AI Act illustrates regulatory initiatives intended to guarantee the safe and ethical utilization of AI.

The EU AI Act establishes strict requirements for high-risk AI applications, prioritizing transparency, accountability, and human oversight. Compliance to these standards is essential for firms operating in the EU and those who engage in EU markets (Goodman & Flaxman, 2017). The Act promotes organizations to adopt a proactive approach on AI governance by identifying high-risk AI systems and promoting AI literacy and awareness among employees. Organizations that sign the AI Pact commit to implementing the principles of the AI Act immediately, ensuring preparedness for its complete enforcement while fostering trust and transparency in AI systems (European Commission, 2024).

The lack of standardization contributes to the issues of AI integration. The rapid development of AI technology has far surpassed the development of industry standards, resulting in uncertainty on best methods for setting up and handling of AI systems. The difference prevents organizations from effectively investing in AI solutions (Van Stein et al., 2023). The issues of liability and accountability for decisions or failures caused by AI remain unsolved. Ensuring responsibility in cases of network disruptions or incorrect configurations caused by AI systems is complex, especially when different stakeholders are involved (Ismanov et al., 2024).

2.2 Review of Key Studies

This section an examination of research related to incorporating AI, especially in the field of network engineering. This review showcases discoveries and breakthroughs from studies, offering insights into the current state and potential advancements of AI applications.

2.2.1 Ethical AI and Fairness

Mehrabi et al. (2019) conducted a comprehensive survey on bias and fairness in machine learning addressing the ethical challenges presented by AI systems. Their research systematically examined different forms of biases that potentially have the ability to impact machine learning models, such as selection bias, measurement bias, and algorithmic bias. The researchers put forward approaches to identify and address these biases with a focus, on ensuring fairness and transparency, in intelligence (Mehrabi et al., 2019).

C. Huang et al. (2023) explored the considerations surrounding AI emphasizing the importance of establishing guiding principles and frameworks to foster the ethical advancement of AI technologies. Their research covered key ethical concerns, including data privacy, algorithmic transparency, and accountability. Furthermore C. Huang et al. (2023) underscored in their work the necessity of cooperation to navigate the complexities associated with AI implementation and proposed guidelines for the responsible deployment of AI technologies (M.-H. Huang & Rust, 2018).

2.2.2 Industry Applications and Case Studies

Leitão and Karnouskos (2015) explored how AI is used in environments with a focus on agents functions for optimizing manufacturing processes and enhancing decisions making abilities as well as operational efficiency improvements illustrated through case studies from different industries demonstrating the advantages and obstacles associated with AI adoption (Leitão & Karnouskos, 2015).

Moro-Visconti (2024) delved into AI-driven industry applications, exploring how these technologies are reshaping different sectors such as healthcare, finance, and telecommunications. This research highlighted the diverse applications of AI demonstrating its potential to drive innovation, improve productivity, and create new business opportunities (Moro-Visconti, 2024).

Nti et al. (2022) conducted a review of how AI is used in engineering and manufacturing fields to outline the advancements and challenges in the industries adoption of these technologies. Their research highlighted AI methods, such as machine learning and deep learning that are utilized to improve engineering processes. The researchers emphasized the need for exploration and innovation to fully leverage the potential of AI in engineering and manufacturing endeavors (Nti et al., 2022).

Balmer et al. (2020) delved into the use of AI, in telecommunications and related network sectors which uncovered AI applications, as maintenance and traffic control for 5G networks. The study showcased the efficiency gains and time savings from using AI while also addressing the regulatory hurdles that come with integrating AI into network industries (Balmer et al., 2020).

2.2.3 Regulatory Challenges

Voigt and Von Dem Bussche (2017) provided an in-depth analysis of the GDPR and its implications for AI. Their research delved into the necessity of data protection measures, transparency, and accountability, emphasizing the need for organizations to comply with GDPR when developing and deploying AI systems. The researches also shed light on the challenges and opportunities that are presented from the GDPR regulations when applied to AI systems (Voigt & Von Dem Bussche, 2017).

Cath (2018) delved into the ethical, legal, and technical challenges associated with governing AI. The paper investigated the aspects the regulatory landscape for AI and shed light on the responsibilities of diverse stakeholders in ensuring ethical AI development and social implications of AI (Cath, 2018).

In conclusion, these key studies offer perspectives on the ethical considerations, industry applications, and regulatory challenges associated with AI. They highlight the transformative potential of AI while emphasizing the need tackle the ethical and operational hurdles for an efficient integration of AI.

2.3 Research Gaps

While existing literature highlights the transformative capabilities of AI in network engineering and consulting, a few critical gaps remain. These gaps are especially relevant when considering the research questions stated in chapter 1.4. This section highlights areas of insufficient research, identifying possibilities to enhance current knowledge and aligning these gaps with the aim of the thesis.

2.3.1 Limited Research on AI for Customized Network Designs

The utilization of AI in standard engineering tasks, including network configuration and fault detection, has been thoroughly examined. However, research addressing its function in meeting customized network design specifications are somewhat limited. Customized designs frequently require a compromise of opposing objectives, such as reducing costs while enhancing performance and energy efficiency, requiring an additional level of expertise than standard tasks (C. Huang et al., 2023). Additionally, the scalability of AI tools for customized enterprise-level solutions with complex interdependencies is still insufficiently explored (Van Stein et al., 2023). This gap aims to assess AI's effectiveness in managing non-standard, client-specific designs and the limitations that engineers encounter in these situations. Addressing this gap will clarify how AI can manage the complex aspects of customization while identifying areas for improvement in its use. This gap investigates the practical implications of AI in engineering workflows, emphasizing measurable advantages. By addressing this gap, the thesis can assess the practical usefulness of AI in both standardized and customized tasks, providing meaningful insights on its economic and operational contributions.

2.3.2 Insufficient Integration of Ethical and Regulatory Frameworks

Although ethical and regulatory challenges associated with AI adoption, such as data privacy, algorithmic transparency, and accountability, are frequently discussed, practical frameworks for addressing these challenges remain underdeveloped. The EU AI Act sets strict requirements for compliance for high-risk AI applications; however, there is little guidance on integrating these regulations into current processes without disrupting efficiency (European Commission, 2024). This gap addresses sub-question 4, which explores the ethical and regulatory challenges encountered by network engineers and consultants in the integration of AI into their processes. This paper aims to offer practical advice for aligning the implementation of AI with emerging regulatory frameworks while maintaining operational efficiency.

2.3.3 Skill Gaps and Human-AI Collaboration

AI technologies require specialized knowledge in fields such as machine learning, data science, and software engineering, which many network engineers and consultants lack. Although the literature acknowledges these skill gaps, limited research provides practical ways for minimizing them or explores the optimization of human-AI collaboration within engineering workflows (Gomez-Carmona et al., 2022). Comprehending how engineers may proficiently collaborate with AI technologies is crucial for realizing AI's full potential in network engineering.

This gap emphasizes improving efficiency, accuracy, and collaboration in standard engineering activities. Addressing this challenge will offer insights into techniques for bridging skill gaps and enhancing collaboration between engineers and AI systems.

2.3.4 Excluded Gaps

Although there are more gaps than mentioned, such as quantifiable evidence on time and cost savings, dynamic network conditions, standardization, and long-term workforce impacts, are also important, these gaps fall outside the scope of this thesis' primary focus. These gaps relate mostly to overarching industry trends and infrastructure challenges rather than the objectives of this thesis, which focus on efficiency, customization, and regulatory factors.

The selected gaps, customized network design, quantifiable time and cost savings, ethical and regulatory frameworks, and skill gaps, are aligned with the research questions and objectives of this thesis. This thesis aims to advance the understanding of how AI can enhance efficiency, manage customization, and navigate challenges in network engineering and consulting processes. These gaps establish a basis for analyzing the opportunities and limitations of AI, contributing to the broader discourse on its integration into network engineering practices.

2.4 Conceptual Framework

A conceptual framework has been developed that structure the understanding of the relation between AI, its outcomes, and the challenges influencing its adoption.

Key Variables

1. **Independent Variable: AI Role in Network engineering**

   This variale shows how AI technologies are utilized in network engineering processes to improve performance. The variable has three subvariables, these are broken down into the following:

   - **Perceived Usefulness of AI in Real-Time Optimization**: This refers to the extent that AI is seen as beneficial in dynamically adjusting network parameters.
   - **Percentage of Tasks Automated by AI**: This measures the percentage of standard tasks which are automated by AI systems.
   - **Precision of Predictions for Equipment Failures and Downtime Reduction**: This refers to how accurate AI systems can predict failures or potential issues, thus allowing fo failures

2. **Dependent Variables**

   - **Process efficiency**: Improvements in speed of task execution, resource utilization, and overall operational productivity enabled by AI .
   - **Design accuracy**: It is the reduced errors and improved precision and reliability of network engineering outputs, especially for complex, client-specific designs.

3. **Moderating Variables**

   - **Regulatory Compliance**: This variable refers to the compliance to laws, regulations, and industry standards which impact the integration of AI in network engineering.
   - **Perceived Trust**: This variable refers to the confidence network engineers, network consultants, and stakeholders have in AI systems to perform task accurately and reliably.

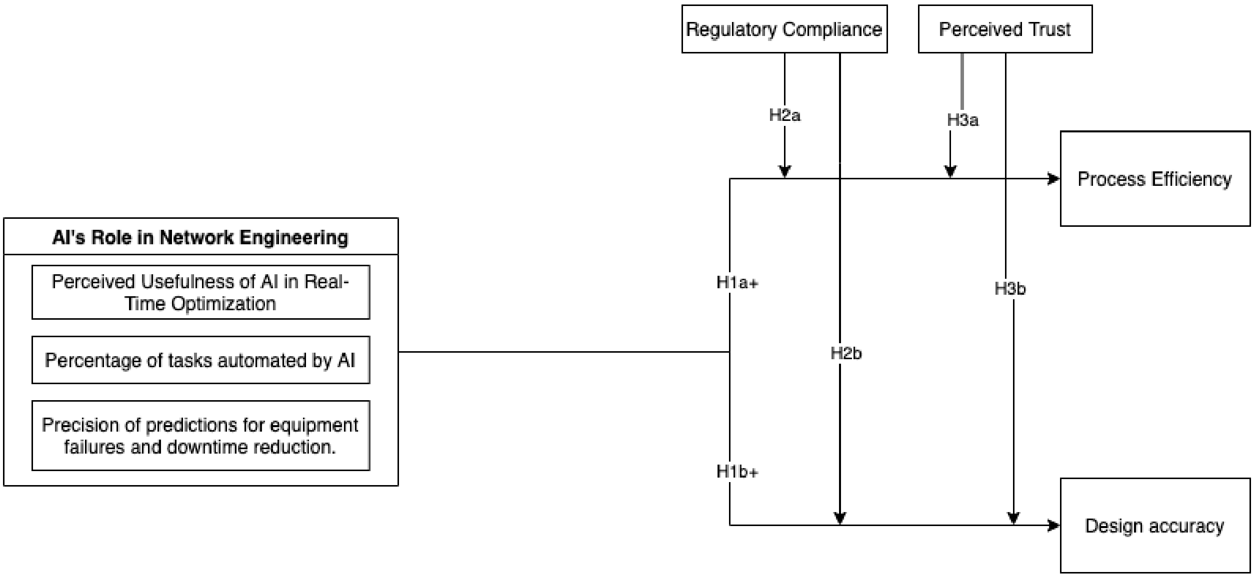

Figure 2.1: Conceptual Framework for AI Utilization in Network Engineering

Hypotheses Overview

The relationship between the variables are shown in the following hypotheses.
H1a: AI's Role in Network Engineering positively influences Process Efficiency.
H1b: AI's Role in Network Engineering positively influences Design Accuracy.
H2a: Regulatory Compliance moderates the relationship between AI and Process Efficiency.
H2b: Regulatory Compliance moderates the relationship between AI and Design Accuracy.
H3a: Perceived Trust moderates the relationship between AI and Process Efficiency.
H3b: Perceived Trust moderates the relationship between AI and Design Accuracy.

Chapter 3

Methodology

This chapter gives a description on the method used in the thesis, including context of the study, data collection method, and data analysis. At first the research will be described, after the data collection method will be explained. Furthermore the steps that are involved in the data analysis will be outlined. Concluding this chapter is a discussion of the validity and trustworthiness of the thesis.

3.1 Research Context

Network design and engineering processes have become increasingly complex, posing considerable challenges for professionals who must solve tasks with highly customized requirements. In contrast to standardized tasks that can be performed according to fixed templates and guidelines, custom tasks generate the need for customized solutions that take in to account specific customer requirements, unique technical constraints, and the rapidly changing environments. Network engineers and consultants, must draw on technical expertise, creativity, and precision under time and resource constraints to make this level of complex work.

AI has emerged as a game-changing technology with the potential of enabling professionals to tackle these issues. In this regard, AI tools ranging from machine learning and predictive analytics to intelligent simulation engines have offered promising assistance in customized network design and engineering tasks, from determining the right configurations, creating personalized recommendations, to taking on the complex due diligence over large piles of contextual data. The use of AI to automate in areas such as optimizing network performance and generation customized solutions hasn't been fully explored, just as the potential of AI in supporting customized tasks has not been realized yet.

This thesis, uses KPN, a leading telecommunications and IT provider for the Dutch market, as an important reference. KPN delivers complex and custom network solutions and has the challenge of maintaining efficiency while meeting client-specific demands. The goal of this research is to describe in which way AI can assist network engineers and consultants in improving the efficiency and accuracy of processes related to customized network design and engineering. Through a focus on the opportunities and challenges unique to this context, the study aims to provide insights into actionable takeaways for those professionals engaged in these complex tasks, but also to inform the development of AI tools that might be better aligned to addressing highly customized requirements.

3.2 Data Collection

This thesis employs a mixed-method research design and helps to determine how much AI can help network engineers and consultants in making more effective and precise design and engineering processes while also catering to standardized and customized requirements. Mixed-method designs combine both quantitative and qualitative approaches, offering the best of both worlds by combing both both data that is measurable and insights from experiences of experts (Creswell, 1999).

3.2.1 Quantitative Data Collection

For the quantitative part, a survey has been conducted to 30 respondents. To determine an appropriate sample size for the survey, the sample size formula is used, as shown in equation 3.1

$$n = \frac{Z^2 * p * (1 - p)}{e^2} \tag{3.1}$$

Where n is the required sample size, Z stands for the Z-value, for a 95% confidence level 1.96 is used, p is the estimated proportion of the population, since the exact proportion is unknown 0.5 is used to maximize the variability. e stands for the margin of error, in this case it is 0.1. Applying this formula results in a sample size of 96 respondents. However, considering the nature of the research, time constraints and the access to specialized professionals, network consultants and network engineers, a smaller sample size of 30 to 50 respondents is considered both practical and sufficient to identify trends and relationships within the data (Taherdoost, 2016).

Survey Design

The survey consist of mainly closed-ended questions with the exception of the last two questions to facilitate the collection of quantitative data to define how AI is helping network engineers and consultants in improving efficiency and accuracy. Responses were be quantified based on a 5-point Likert scale. the surveys consists of the following sections; (i) background and experience, (ii) perception of AI in network engineering, (iii) AI for efficiency and time-saving, (iv) AI for accuracy and error reduction, (v) customization and adaptability, (vi) potential challenges with AI integration, (vii) anticipated impact on job satisfaction and role changes, (viii) future of AI in network engineering, (ix) attitude and usage intentions. Detailed scale variations and the complete survey questionnaire are provided in Appendix A.

Survey Distribution

Qualtrics was used to create the survey, and it was sent out via Linked In, email, Microsoft Team, and WhatsApp. These platforms are selected because of the broad reach and ability to efficiently target the required professionals. Participants were recruited through professional networks, industry associations, and social media channels. The survey was active in the months of October and November 2024.

3.2.2 Qualitative Data Collection

According to Guest et al., 2006 data saturation can be reached with six to twelve interviews. The twelve people were selected based on their knowledge of network engineering, network consultancy, automation or AI. For the qualitative part, twelve semi-structured interview were be conducted. Qualitative data was be collected alongside quantitative data through semi-structured interviews. It combines structure with non-structure, allowing pre-decided questions while also providing the opportunities for emergent themes (Fontana & Frey, 2000). Semi-structured interviews are quite suitable to reflect the complexity and richness of participants experience and perspectives.

Sampling Strategy

Participants had relevant experience and knowledge that were informed by a purposive sampling strategy. According to Guest et al. (2006), this non-probabilistic sampling technique is often employed in qualitative research and "ensuring that the sample is information-rich, relevant to the research questions." There in total there were four network engineers, two network consultants, one network engineer and consultant, one general mangers of network engineers, one manager with the knowledge of use of AI in security, one automation manager, one process manager, and one cybersecurity specialist interviewed. The profiles of the interviewees are shown in table 3.1.

Data Saturation

The concept of data saturation was used to find whether the sample size was adequate or not. Data saturation is reached when no further information or themes are found in the data (Guest et al., 2006). According to the results of Guest et al. (2006) found saturation within the first twelve

Table 3.1: Interviewees Profile

Function	Company	Branche	Years of Experience	Date
Network Engineer	A	Telecommunications	27	13/11/2024
Manager Network Engineers	A	Telecommunications	22	13/11/2024
Process Manager	A	Telecommunications	18	14/11/2024
Manager AI	B	Telecommunications	20	14/11/2024
Network Engineer	A	Telecommunications	9	15/11/2024
Automation Manager	A	Telecommunications	12	15/11/2024
Network Engineer	A	Telecommunications	31	18/11/2024
Network Engineer/Consultant	C	Telecommunications	10	18/11/2024
Network Consultant	A	Telecommunications	27	19/11/2024
Network Consultant	A	Telecommunications	24	20/11/2024
Cybersecurity Specialist	D	Cybersecurity	12	21/11/2024
Network Engineer	A	Telecommunications	16	22/11/2024

interviews, with basic elements for metathemes found in as few as six interviews. This method guaranteed that the sample size was large enough to include the breadth and depth of the data without redundancy.

Interview Process

Interviews were held in a supportive and confidential environment to promote candid and honest communication, this meant that the interviews were held either via MS Teams or in person, depending on the interviewee's preference. The interviews lasted between 30 to 60 minutes in length and were recorded with the consent of the participants. In addition to these individual interview notes were prepared to summarize the main points made from the recorded transcripts. Transcripts were generated by the transcription tool available through MS Teams for online interviews and additionally, transcribing was assisted via AmberScript for onsite interviews.

The interview started with introduction questions such as what their role is, at what company their, and the years of experience in the telecommunications sector. The questions shown in table 3.2 were tailored according to what was aimed to research, it was important to understand how AI can help network engineers and consultants in improving the efficiency and accuracy of design and engineering processes, In the interviews, other, more specific questions were adapted according to the participants' answers to the standard questions. This adaptive approach enhanced the analysis by providing a deeper understanding of the nuances in AI's role within customized network engineering and consultancy requirements, ultimately enriching the overall output. These questions were crucial for answering this thesis' main research question.

Table 3.2: Interview Questions

Interview Section/Part	Questions	Objective
Efficiency, Accuracy, and Collaboration in Standard Engineering Tasks	• How would you describe the current efficiency and accuracy in your standard engineering tasks? • What collaboration challenges do you experience when performing these tasks? • How do you think AI can play a role in improving efficiency, accuracy, and collaboration within these tasks?	To understand how AI contributes to improving standard engineering processes and addressing collaboration challenges.
Support for Customization and Limitations of AI	• How often do you encounter situations where specific client requirements demand customization? • What limitations do you currently experience when using AI to support customization? • To what extent do you think AI could help more effectively support these customization requirements?	To gain insight into how AI can support customization and the limitations faced by engineers and consultants.
Time and Cost Savings through AI	• What potential time and cost savings do you think AI could bring to standard engineering tasks? • Do you think AI could also provide benefits in terms of cost savings for customization requirements? If so, how?	To explore the potential advantages of AI in terms of time and cost savings for both standard and customization requirements.
Technical, Ethical, and Regulatory Challenges	• What technical, ethical, or regulatory challenges do you experience when integrating AI into your work? • How do you think these challenges could influence the future use of AI?	To understand the barriers and risks that might hinder AI integration and the long-term impact on the work of engineers and consultants.

3.2.3 Ethical Considerations

In relation to data collection for both the survey and the interview ethical considerations were key. The participants were fully informed about the scope of the study and were told that their participation was voluntary, that it was possible for them to withdraw from the study at any time, and that they would not be penalized in any way if they chose to withdraw. Confidentiality and anonymity were strictly maintained to protect participants' privacy. All the data is stored securely and only accessible by the researcher.

Informed consent was verified electronically prior to administering the survey. Participants were presented with the following privacy statement: This survey did not collect any personally identifiable information beyond the answers to the survey questions. All data gathered was be used exclusively for the purpose of a master's thesis for the MSc Information Management program, conducted by the Department of Information Systems and Operations Management at Tilburg School of Economics and Management, Tilburg University. Participation is voluntary, and respondents have the right to withdraw at any time without penalty. All responses will be kept confidential and stored securely.

For interviews informed consent was obtained prior to beginning the interview. Risks such as discomfort in the process of sharing personal or professional experiences were mitigated through creating a safe and respectful environment for all participants. All participants were also informed that their responses would only be used for research purposes, and their identities kept confidential.

3.3 Data Analysis

3.3.1 Quantitative Data Analysis

Quantitative data that was collected through the survey was be analyzed using the Statistical Package for Social Sciences (SPSS) software, in a systematic manner:

1. **Data cleaning and preparation:** Survey responses were imported into SPSS. All partial or inconsistent responses were found and filled out. This step deals with missing values, data quality control for duplicate and missing values, this verifies that all entries are correctly formatted.

2. **Descriptive Statistics:** A descriptive statistic were calculated first to summarize the dataset. Measures such as means, medians standard deviation, and frequency distribution provided a description of respondent demographic characteristics and survey question response options.

3. **Inferential Statistics:** Inferential statistical methods were used to inspect the relationships between variables. To assess differences and associations between groups, standard test of significance — t-test, chi-square test and ANOVA — was used where appropriate.

4. **Regression Analysis:** Regression analysis takes place to see if there are predictive relationships between dependent and independent variables. This would allow for assessing the influence of some factors on some important outcomes in network management.

5. **Results Visualization:** Results were visualized using tables to facilitate interpretation and improve findings presentation. The visualization was to help make sense of complex data and provide a clear overview of important trends and patterns.

3.3.2 Qualitative Data Analysis

A thematic analysis was used on the interview data. Transcripts were coded with the help of Microsoft CoPilot to identify recurring patterns and themes. Coding followed an inductive methodology, allowing themes to emerge organically from the data rather than being pre-determined. Key themes identified included:

- **Efficiency and Accuracy in Engineering Tasks:** Insights into current inefficiencies and the role of AI in addressing these.

- **Customization Challenges and Opportunities:** Perspectives on how AI can support client-specific requirements.

- **Economic Impacts:** Time and cost savings potential of AI in standard and customized tasks.
- **Integration Barriers:** Technical, ethical, and regulatory challenges faced during AI adoption.

3.4 Notion of AI

This thesis acknowledges the use of AI tools based on LLM's, such as ChatGPT, Grammerly, and CoPilot, have been used to help with specific parts of the research and its writing process. The tools were used for clarifying and refining ideas, this helped the researcher to make a few ideas and results more clear and easier to understand. All the recommendations have been carefully considered by the researcher. The design, analysis, and findings of the thesis were developed by the researcher in order to maintain its originality and academic integrity. This section is included to be transparent about the use of AI tools while also making clear that the research and writing was done by the researcher.

Chapter 4

Data Analysis and Results

This chapter presents the data that was collected during the survey and interviews, the analysis of these results and finally the discussion of findings. The data will be presented within each category, and if necessary the qualitative data from the survey will be used to back up the claim or explain if it would also be divided.

4.1 Quantitative Data presentation

This section shows the data from the survey divided in four themes: efficiency, accuracy, and collaboration in engineering tasks; support for customization and limitations of AI; time and cost savings through AI; technical, ethical and regulatory challenges.

4.1.1 Efficiency, Accuracy, and Collaboration in Engineering Tasks

Current Operational Efficiency in Engineering Tasks

In this subsection the role AI in improving the efficiency and accuracy of standard engineering tasks is explored. The results shows the participants' overall perceptions and relationships between efficiency and accuracy, and the influence of transformative AI applications. The descriptive statistics show moderately positive perceptions of the impact AI has on efficiency and accuracy. The mean for efficiency was 3.43 and standard deviation was 0.728, the mean for accuracy was lower at 3.33 and standard deviation was 0.802, this is also shown in table 4.1.

Table 4.1: Descriptive Statistics for Efficiency and Accuracy

Variable	Mean	Std. Deviation	Min	Max
ImproveEfficiency (Q8)	3.43	0.728	2	5
ImproveAccuracy (Q9)	3.33	0.802	1	5

Correlating AI Implementation with Improved Accuracy

For the correlation analysis it showed a significant positive correlation between perceptions of AI's impact on efficiency and accuracy, r=0.571 and p¡0.0001. This suggests that participants that perceive AI as improve efficiency are also likely to see improvements in accuracy. The correlation matrix is shown in table 4.2.

Table 4.2: Correlation Matrix for Efficiency and Accuracy

Variables	**ImproveEfficiency (Q8)**	**ImproveAccuracy (Q9)**
ImproveEfficiency (Q8)	1.00	0.571**
ImproveAccuracy (Q9)	0.571**	1.00

$^{**}p < 0.01$

AI's Role in Fostering Collaborative Efficiency

For the regression analysis it was tested whether transformative AI applications in network engineering predict improvements in efficiency and accuracy.

For efficiency, the regression model showed that it was statistically significant, F=7.054, p=0.013, and it explained 20.1% of the variance. β coefficient for Q10 was 0.449, this indicated a significant positive effect on efficiency. The regression coefficients are shown in 4.3.

For accuracy, the model was not significant, F=1.617, p=0.214, and only explained 5.5% of the variance. Q10 only had a non-significant β coefficient of 0.234.

The model summary and ANOVA are shown in C.

Table 4.3: Regression Coefficients for Efficiency and Accuracy

Dependent Variable	**Predictor**	**B**	**Beta**	**t**	**p**
ImproveEfficiency (Q8)	TransformNetworkEngineering	0.449	0.449	2.656	0.013*
ImproveAccuracy (Q9)	TransformNetworkEngineering	0.234	0.234	1.272	0.214

$^{*}p < 0.05$

4.1.2 Support for Customization and Limitations of AI

Adaptability to Client Needs

The analysis showed the participants' perception of AI's adaptability to handle client-specific requirements. The descriptive analysis, shown in table 4.4, this indicates that participants moderately agree with the statement that AI is adaptable to client needs, with a mean score of 3.4 and a standard deviation of 0.7. this suggest that while AI tools are seen as somewhat effective there is still room for improvement in addressing the nuances of customized tasks.

Regression analysis showed that familiarity with AI tools is a significant predictor of perceptions of adaptability, F=5.67, p=0.005, explaining 12% of the variance. The β coefficient for familiarity was 0.29 with p=0.02, this indicates that participants with familiarity perceive AI as more adaptable to specific client needs. This is shown in table 4.5, with detailed statistics shown in appendix D.

Table 4.4: Descriptive Statistics for Customization Needs

Variable	**Mean**	**SD**	**Range**
AdaptabilityToClientNeeds	3.4	0.7	2-5

Table 4.5: Regression Coefficients for Familiarity with AI Predicting Adaptability

Predictor	**B**	**Beta**	**t**	**p**
FamiliarityWithAI	0.29	0.29	2.45	0.02*
Constant	2.8	-	-	-

$F(2, 78) = 5.67$, $p = 0.005$, $R^2 = 0.12$. $^{*}p < 0.05$.

Role of Familiarity and Trust

According to the analysis, trust plays a significant role in how participants perceive AI's ability to support customized tasks. The descriptive analysis has a mean score of 3.5 and a standard deviation of 0.6 for perceived trust in AI for customization. This is shown in table 4.6. The correlation showed a significant positive relationship between familiarity with AI and perceived trust, R=0.53, p<0.001. This suggests that participants who are more familiar with AI tools are more likely to trust these tools to handle customized tasks effectively. Additional detailed correlations are provided in appendix D.

Table 4.6: Descriptive Statistics for Trust in AI

Variable	**Mean**	**SD**	**Range**
TrustInAI	3.5	0.6	2-5

Experience Levels and Customization

The years of experience of the participants influence their perceptions of AI's ability to support customization. Regression analysis found a significant negative relationship between experience levels and perceptions of AI's customization support, F=4.89, p=0.03, the β coefficient was -.022, p=0.03, this indicates that participants with more experience rated that AI's customization support slightly lower, potentially showing greater awareness of its limitations. This is shown in table 4.7, the complete regression details are shown in appendix D.

Table 4.7: Regression Coefficients for Experience Predicting Customization Support

Predictor	**B**	**Beta**	**t**	**p**
ExperienceYears	-0.22	-0.22	-2.21	0.03*
Constant	3.6	-	-	-

*$F(1, 79) = 4.89$, $p = 0.03$, $R^2 = 0.06$. *$p < 0.05$.*

4.1.3 Time and Cost Savings Through AI

Overview of Time and Cost Insights

The descriptive analysis shows an overview of the perceptions regarding time and cost savings facilitated by AI implementation. For time savings the mean score was 3.43 with a standard deviation of 0.738, this indicates a moderately positive perception of AI's contribution to saving time in engineering tasks. For cost savings the mean score was 3.33 with a standard deviation of 0.803, this suggest a similar positive perfection. For the details of the table refer to table 4.8.

Table 4.8: Descriptive Statistics for Time and Cost Savings

Variable	**Mean**	**Std. Deviation**	**Min**	**Max**
Time Savings	3.43	0.738	2	5
Cost Savings	3.33	0.803	2	4

Impact of AI Familiarity and Usage on Savings

The correlation analysis shows the relationship between time savings, cost savings, familiarity with AI, and AI usage. Among all the variables there were positive correlations. Time savings and cost savings had r=0.571 with p<0.001, familiarity with AI and time savings had r=0.664 with p<0.001, AI usage and cost savings had r=0.484 with p=0.007. The results are shown in table 4.9. Participants who are more familiar with AI make more use of it perceived higher time and cost savings, this suggests that increased exposure to AI can improve its perceived efficiency.

Table 4.9: Correlation Matrix for Time and Cost Savings

Variables	Time Savings	Cost Savings	Familiarity with AI	AI Usage
Time Savings	1.00	0.571**	0.664**	0.600**
Cost Savings	0.571**	1.00	0.485**	0.490**
Familiarity with AI	0.664**	0.485**	1.00	0.504**
AI Usage	0.600**	0.490**	0.504**	1.00

**p < 0.01

Associations Between Familiarity, Usage, and Savings

There were two regression models had been conducted, this was to examine wether familiarity with AI and AI usage predict perceptions of time savings and cost savings.

For the first model predicting time savings, the model was significant with F=15.564 with p <0.001 and explains 54.6% of the variance. Familiarity with AI had B=0.323, β=0.486, t=3.198, p=0.004. AI Usage had B=0.295, β=0.355, t=2.339, p=0.027. For the second model predicting cost savings. This model was also significant, F=6.241, p=0.006 and explains 31.6% of the variance. Familiarity with AI had B=0.234, β=0.391, t=1.731, p=0.095. AI Usage had B=0.302, β=0.330, t=1.789, p=0.085. The results are shown in table 4.10.

Table 4.10: Regression Coefficients for Time and Cost Savings

Dependent Variable	Predictor	B	Beta	t	p
Time Savings	Familiarity with AI	0.323	0.486	3.198	0.004*
Time Savings	AI Usage	0.295	0.355	2.339	0.027*
Cost Savings	Familiarity with AI	0.234	0.319	1.731	0.095
Cost Savings	AI Usage	0.302	0.330	1.789	0.085

*p < 0.05

4.1.4 Technical, Ethical, and Regulatory Challenges

Insights into AI-Related Concerns

The descriptive analysis showed insights into perceptions of technical, ethical, and regulatory challenges when integrating AI. the concerns regarding security and data privacy risk had a mean score of4.21 and a standard deviation of 0.87, this shows an agreement on its significant. Lack of understanding of AI technology also showed a mean score of 3.87 and a standard deviation of 0.92, this indicates a moderate agreement on this challenge. The table is shown in table 4.11.

Table 4.11: Descriptive Statistics for Technical, Ethical, and Regulatory Challenges

Variable	Mean	Std. Deviation	Min	Max
Security and Data Privacy Risks	4.21	0.87	2	5
Lack of Trust in AI Accuracy	3.65	0.91	2	5
High Implementation Costs	3.72	0.89	2	5
Lack of Understanding of AI Technology	3.87	0.92	2	5
Challenge Integrating AI	3.91	0.88	2	5

Exploring Relationships Among Challenges

The correlation analysis showed the significant relationships between the variables. Security and data privacy risks positively correlated with challenge integrating AI, with r=0.612 and a p <0.01. High implementation costs correlated with lack of trust in AI Accuracy with r=0.543 and p <0.01.

The table is shown in table 4.12

Table 4.12: Correlation Matrix for Technical, Ethical, and Regulatory Challenges

Variable	1	2	3	4	5
1. Security and Data Privacy Risks	1.00	0.612**	0.521**	0.456**	0.592**
2. Lack of Trust in AI Accuracy	0.612**	1.00	0.543**	0.489**	0.567**
3. High Implementation Costs	0.521**	0.543**	1.00	0.503**	0.538**
4. Lack of Understanding of AI Technology	0.456**	0.489**	0.503**	1.00	0.521**
5. Challenge Integrating AI	0.592**	0.567**	0.538**	0.521**	1.00

**$p < 0.01$

Predictors of AI Integration Challenges

The regression model was constructed to predict challenge integrating AI, this was based on familiarity with AI, AI usage, and specific concerns. The model was significant with F=11.456, p<0.001 and it explained 63.2 % of the variance.
The key predictors were security and data privacy risk, and lack of understanding of AI technology. Security and data privacy risk had B=0.423, β=0.428, p=0.003. Understanding of AI technology had B=0.271, β=0.329, p=0.027. This is shown in table 4.13.

Table 4.13: Regression Coefficients for Technical, Ethical, and Regulatory Challenges

Dependent Variable	Predictor	B	Beta	t	p
Challenge Integrating AI	Security and Data Privacy Risks	0.423	0.482	3.341	0.003**
Challenge Integrating AI	Lack of Understanding of AI Tech.	0.271	0.329	2.239	0.027*
Challenge Integrating AI	Lack of Trust in AI Accuracy	0.164	0.187	1.556	0.132
Challenge Integrating AI	High Implementation Costs	0.192	0.204	1.645	0.111

**$p < 0.01$, *$p < 0.05$

4.2 Qualitative Data presentation

This section shows the data from the interviews divided in four themes: efficiency, accuracy, and collaboration in engineering tasks; support for customization and limitations of AI; time and cost savings through AI; technical, ethical and regulatory challenges. The summaries per question are shown in B.

4.2.1 Efficiency, Accuracy, and Collaboration in Engineering Tasks

This section summarizes interviewees' perspectives, highlighting inefficiencies in manual processes, disconnected workflows, and inconsistent configurations, while emphasizing the potential of AI-driven tools to enhance efficiency and accuracy. The summary of the key insights are shown in table 4.14.

Current Efficiency and Accuracy

The participants have identified a few challenges impacting the efficiency and accuracy of standard engineering tasks. Interviewee H has described the scalability of standard products while emphasizing inefficiencies which are caused by redundant management and the frequent reuse of templates which are prone to errors. He has stated that: *"The templates we use are often outdated or unvalidated, and when reused, they lead to unnecessary errors."* Interviewee H emphasized the necessity for better integration of configurations to minimize the redundancies and ensure consistency. Interviewee H also observed inefficiencies stemming from the dependence on manual configurations, stating *"A lot of the configuration work is still manual, and that's where we see the most errors and time wasted."*

Interviewee I assessed the efficiency and accuracy of current processes within the company as a "6" highlighting disconnected knowledge and frequent handovers as a key issue. Interviewee I stated:*"Knowledge is scattered across teams, and when one team hands over to another, mistakes are often made because there's no unified process."*. Interviewee C highlighted the importance of accurate starting data, stating: *"Automation works only as well as the data you feed it. For things like SD-LAN or SD-WAN, if the input data is bad, the results are suboptimal."*

These findings indicate that although scalability is achievable, inefficiencies predominantly stem from manual processes, inconsistent configurations, and separated processes. Utilizing automated tools and AI-driven validation mechanisms could significantly enhance efficiency and accuracy.

Collaboration Challenges

Challenges in collaboration appeared as a recurring topic in the responses. Interviewee H noted challenges in achieving support for data-driven approaches among team members, stating: *"There's a lot of skepticism about using data-driven methods, especially among senior engineers who are used to traditional workflows."* Interviewee also described a misalignment between management objectioves and operational realities, stating: *"Management often pushes for quick results, but they don't align with what's possible on the ground. This disconnect creates friction."*

Interviewee L observed insufficient communication between teams, which negatively impacted collaboration. Interviewee L stated: *"Different teams work in silos, and there's little coordination when it comes to delivering a seamless client experience."* Interviewee E emphasized the risks during trainsitions between teams, stating: *"When one team finishes their part and hands it over to the next, it's almost guaranteed that something will be missed or miscommunicated."*

These observations indicate that collaboration obstacles encompass not just technical issues but also include cultural and organizational factors. Interviewees suggested that AI may significantly contribute to overcoming these difficulties by enhancing data sharing, standardized workflows, and delivering actionable insights to improve coordination.

Role of AI in Improving Efficiency, Accuracy, and Collaboration

Interviewees agreed that AI has the potential to enhance efficiency, accuracy, and collaboration in standard engineering tasks. Interviewee H emphasized the significance of fostering a data-driven work culture, stating, *"AI tools can help us analyze data more effectively, optimize workflows, and reduce redundancies." He added, "Machine learning models, for example, can predict configuration issues before they even occur, saving us a lot of rework."*

Interviewee C highlighted AI's ability to validate configurations and improve collaboration, explaining, *"AI can check configurations in real-time and flag inconsistencies, which reduces manual errors and speeds up the process."* Interviewee C also observed the potential of AI to improve collaboration through workflow standardization, stating, *"If AI tools can create a shared framework for all teams to work within, it would eliminate a lot of the communication gaps we currently face."*

These findings highlight AI's ability to address both technical and organizational inefficiencies. Through automating repetitive tasks, ensuring uniform setups, and enhancing communication, AI has the potential to foster a more integrated and efficient engineering environment.

Table 4.14: Summary of Key Insights on Efficiency, Accuracy, and Collaboration in Engineering Tasks

Category	Key Insights	Supporting Quotes
Current Efficiency and Accuracy	Manual processes, redundant workflows, and knowledge disconnection are major inefficiencies.	"The templates we use are often outdated or unvalidated, and when reused, they lead to unnecessary errors." "A lot of the configuration work is still manual, and that's where we see the most errors and time wasted." "Knowledge is scattered across teams, and when one team hands over to another, mistakes are often made because there's no unified process." "Automation works only as well as the data you feed it. For things like SD-LAN or SD-WAN, if the input data is bad, the results are suboptimal."
Collaboration Challenges	Poor communication, lack of buy-in, and misaligned objectives hinder effective collaboration.	"There's a lot of skepticism about using data-driven methods, especially among senior engineers who are used to traditional workflows." "Different teams work in silos, and there's little coordination when it comes to delivering a seamless client experience." "When one team finishes their part and hands it over to the next, it's almost guaranteed that something will be missed or miscommunicated."
Role of AI in Improvements	AI can automate tasks, validate configurations, and enhance data-driven decision-making to improve efficiency and collaboration.	"AI tools can help us analyze data more effectively, optimize workflows, and reduce redundancies." "AI can check configurations in real-time and flag inconsistencies, which reduces manual errors and speeds up the process." "If AI tools can create a shared framework for all teams to work within, it would eliminate a lot of the communication gaps we currently face."

4.2.2 Support for Customization and Limitations of AI

This section the various percecpectives of interviewees are summarized, revealing the importance of customization in engineering tasks and the challenges AI faces in supporting these requirements. The summary of the key insights are shown in table 4.15.

Frequency of Customization

Customization requirements are a common occurrence for the majority of the interviewees. Interviewee H noted that enterprise clients, especially large organizations, often require heavily customized designs beyond standard offerings. Interviewee H explained, *"Enterprise clients don't want off-the-shelf solutions; they demand highly tailored designs that address their unique needs."*. Interviewee L emphasized that despite the widespread push towards standardization, customization remains a frequent necessity. Interviewee B stated *"We aim to standardize, but the reality is that most projects end up being customized because no two clients have the same requirements."*. Interviewee I highlighted the necessity of balancing customization with the reuse of standard components, stating *"While we try to leverage standard modules, customization is almost always necessary to meet specific client expectations."*

These responses suggest that customization is a critical element of network engineering, influenced by the diverse requirements of clients.

Current Limitations in AI Support

Participants saw considerable limitations in AI's ability to support customization. Interviewee H highlighted that there is resistance to adopting data-driven methods due to job displacement fear and limited understanding of AI tools' potential. Interviewee H explained, *""Many engineers are hesitant to embrace AI because they feel it might replace them or oversimplify their work."* Interviewee C recognized technical limitations, stating, *"AI tools struggle to adapt dynamically to evolving client requirements without constant human intervention. They're not flexible enough for real-time changes."* Interviewee I added that the effectiveness of AI is hindered by the incomplete datasets and inconsistent inputs, noting *"AI models often rely on clean, structured data, which is rarely the case in real-world scenarios."*

These limitations highlight the need for robust AI tools which are able to adapt to dynamic and complex customization requirements, while also addressing user concerns about job security and technical limitations.

Potential AI Contributions

Despite the current limitations, interviewees expressed optimism about the potential contributions of AI to customization. Interviewee H was especially enthusiastic, stating *"AI has the capacity to simplify complex designs and reduce the likelihood of errors, which is a game-changer in large-scale projects."*. Interviewee J acknowledges the role of AI in standardizing customization, stating *"Even in custom projects, AI can help maintain a level of consistency and reduce the variability that often leads to issues."* Interviewee C discussed the potential of predictive tools, stating *"With the right predictive models, AI could anticipate client needs and dynamically adjust configurations to save time and resources."* Interviewee F added, *"AI-driven simulations could allow us to test various configurations quickly, ensuring we meet specific client demands while minimizing risks."*

These insights suggest that while AI currently faces its limitations, it has the potential to significantly improve customization by optimizing processes, ensuring consistency, and enabling proactive adaptions.

Table 4.15: Summary of Key Insights on AI Support for Customization and Limitations

Category	Key Insights	Supporting Quotes
Frequency of Customization	Customization is frequently required due to diverse client needs, despite efforts to standardize.	"Enterprise clients don't want off-the-shelf solutions; they demand highly tailored designs that address their unique needs." "We aim to standardize, but the reality is that most projects end up being customized because no two clients have the same requirements." "While we try to leverage standard modules, customization is almost always necessary to meet specific client expectations."

Continued on next page

Table 4.15: Summary of Key Insights on AI Support for Customization and Limitations (Continued)

Current Limitations in AI Support	AI tools struggle with dynamic client requirements, incomplete datasets, and skepticism about adoption.	"Many engineers are hesitant to embrace AI because they feel it might replace them or oversimplify their work." "AI tools struggle to adapt dynamically to evolving client requirements without constant human intervention." "AI models often rely on clean, structured data, which is rarely the case in real-world scenarios."
Potential AI Contributions	AI could simplify designs, standardize outputs, and enable proactive adaptations through predictive modeling.	"AI has the capacity to simplify complex designs and reduce errors in configuration. It's not perfect yet, but it's getting there." "Even with customization, AI can create frameworks that help maintain consistency and reduce variability." "With better predictive tools, AI could anticipate client needs and adapt configurations proactively, saving time and effort."

4.2.3 Time and Cost Savings Through AI

This section highlights interviewees' views on AI's ability to save time and costs in both standardized tasks and customization, emphasizing automation, resource optimization, predictive capabilities, while acknowledging constraints in flexibility limitations in highly specific client scenarios. The summary of the key insights are shown in table 4.16.

Standard Engineering Tasks

Interviewees acknowledged the considerable potential of AI to save time and reduce costs in standard engineering tasks. Interviewee E highlighted the reduction of manual labor through automation, stating, *"AI tools can handle repetitive tasks like configuration far faster than any human, and it reduces the chance of errors too."* Interviewee F reiterated this sentiment, explaining, *"By automating mundane processes, we've been able to save hours each week that can now be focused on client-specific issues."* Interviewee L added, *"The time savings from AI-driven tools come not just from task execution but also from avoiding delays caused by human errors."*

In terms of cost savings, interviewee C stated that *"AI enables better resource allocation, avoiding over-provisioning or under-utilization, which has saved us significant operational costs."* Interviewee E elaborated *"With predictive analytics, we can identify and address problems before they escalate, reducing downtime and costly troubleshooting efforts."*

These insights indicate that AI has the potential to significantly improve time and cost savings in standard engineering tasks by automating routine processes, reducing manual labor, and minimizing human error. AI can facilitate optimal resource utilization, optimize workflows, and reduce operational costs, allowing engineers to focus on more strategic and high-value tasks.

Customization Requirements

AI was perceived as a potential tool for achieving time and cost efficiencies in customization tasks, though with more diverse perspectives. Interviewee D highlighted AI's ability to shorten customization cycles, stating *"AI-driven predictive tools can anticipate client-specific needs, helping us adjust configurations faster and with fewer revisions."* Interviewee A added, *"Simulating various configurations with AI allows us to evaluate multiple scenarios quickly, which saves both time and costs."* However interviewee I also noted a limitation, explaining *"Customization still often requires significant manual adjustments because AI isn't flexible enough to handle all client-specific variables."* Interviewee F provided a balanced perspective, stating *"AI does save costs in areas like* *resource optimization, but the upfront investment in training models and integrating systems can offset those savings in the short term."*

These insights suggest that while AI faces its limitation in flexibility and adaptability, it still has the potential to improve time and cost savings in customization tasks. Predictive modeling and simulations facilitate faster project cycles and optimized configurations, minimizing trial-and-error efforts. However, its ability to handle highly specific client needs remains limited, often requiring significant manual intervention to accommodate unique or evolving requirements.

Table 4.16: Summary of Key Insights on Time and Cost Savings Through AI

Category	**Key Insights**	**Supporting Quotes**
Standard Engineering Tasks	AI reduces manual labor, minimizes errors, and optimizes resource allocation, leading to significant time and cost savings.	"AI tools can handle repetitive tasks like configuration far faster than any human, and it reduces the chance of errors too." "By automating mundane processes, we've been able to save hours each week that can now be focused on client-specific issues." "AI enables better resource allocation, avoiding over-provisioning or underutilization, which has saved us significant operational costs."
Customization Requirements	AI can shorten customization cycles, simulate configurations, and optimize resources, though flexibility remains a limitation.	"AI-driven predictive tools can anticipate client-specific needs, helping us adjust configurations faster and with fewer revisions." "Simulating various configurations with AI allows us to evaluate multiple scenarios quickly, which saves both time and costs." "Customization still often requires significant manual adjustments because AI isn't flexible enough to handle all client-specific variables."

4.2.4 Technical, Ethical, and Regulatory Challenges

This section highlights the perspectives of participants regarding the challenges of integrating AI into network engineering, focusing on technical challenges, ethical concerns, and regulatory challenges. Although these obstacles remain significant, they also present opportunity for development of more robust, transparent, and compliant AI solutions. The summary of the key insights are shown in table 4.17.

Technical Challenges

Interviewees identified several technical challenges in integrating AI into network engineering processes. Interviewee C highlighted that the lack of standardization is a significant barrier, stating *"The lack of standardization across systems makes it hard for AI to integrate smoothly."* Interviewee I highlighted the significance of data quality, explaining *"AI models need clean, structured data, but the data we work with is often messy and incomplete."* Similarly, interviewee H highlighted concerns with interoperability, stating *"Interoperability between AI tools and existing workflows is still a significant technical barrier."*

These results indicate that disconnected infrastructure, poor data quality, and integration difficulties are major obstacles to the effective use of AI in network engineering.

Ethical Challenges

Ethical concerns, such as job displacement fears and skepticism about AI adoption, were recurrent themes. Interviewee H explained *"Many engineers are hesitant to adopt AI-driven approaches because they feel it could oversimplify their roles or make them redundant."* Interviewee E added to this by trust issues, stating *"There's a real concern about whether AI decisions can always be trusted, especially when transparency is lacking."*

These insights highlight the importance of addressing workforce concerns and ensuring transparency in AI systems in order to foster trust and acceptance.

Regulatory Challenges

Regulatory compliance has become another significant challenge, especially concerning frameworks like GDPR and the EU AI Act. Interviewee B stated *"The regulatory landscape is always evolving, and it's hard to ensure compliance with AI tools when the rules keep changing."* Interviewee C highlighted the operational complexities introduced by these regulations, stating, *"Meeting the EU AI Act requirements adds a lot of overhead to the implementation process."*

These challenges highlight the need for organizations to navigate complex regulatory frameworks while implementing AI capabilities, ensuring compliance with changing legal and ethical standards.

Table 4.17: Summary of Key Insights on Technical, Ethical, and Regulatory Challenges in AI Integration

Category	**Key Insights**	**Supporting Quotes**
Technical Challenges	AI tools face difficulties with disconnected infrastructure, data quality, and integration with existing systems.	"The lack of standardization across systems makes it hard for AI to integrate smoothly." "AI models need clean, structured data, but the data we work with is often messy and incomplete." "Interoperability between AI tools and existing workflows is still a significant technical barrier."
Ethical Challenges	Job displacement fears and skepticism about AI adoption are significant barriers.	"Many engineers are hesitant to adopt AI-driven approaches because they feel it could oversimplify their roles or make them redundant." "There's a real concern about whether AI decisions can always be trusted, especially when transparency is lacking."
Regulatory Challenges	Compliance with regulations such as GDPR and the EU AI Act creates complexities for AI adoption.	"The regulatory landscape is always evolving, and it's hard to ensure compliance with AI tools when the rules keep changing." "Meeting the EU AI Act requirements adds a lot of overhead to the implementation process."

Chapter 5

Discussion and Interpretation

During the progression of this this thesis, the scope of the research has been refined to focus on the core themes of this research. The research questions were carefully formulated based on an extensive literature review, and supported by a methodological framework. this methodology provided a structured framework for data collection and analysis, establishing a solid foundation for addressing the primary objectives of this thesis.
In this chapter the interpretation of the results, theoretical contributions, practical implications and study limitations will be discussed.

5.1 Interpretation of Results

In this section the meaning and implications of the findings of this thesis will be discussed. These findings will be divided in four themes efficiency, accuracy, and collaboration in standard engineering tasks; support for customization and limitations of AI; time and cost savings through AI; technical, ethical, and regulatory challenges.

5.1.1 Efficiency, Accuracy, and Collaboration in Standard Engineering Tasks

The findings for this theme discuss AI's contribution in improving efficiency and accuracy while exposing ongoing challenges in collaboration. The results offer detailed insights into the dual role of AI: improving operational accuracy and highlighting gaps in team workflows.

Operational Efficiency and Accuracy

Quantitative results highlight the significant positive impact of AI on efficiency and accuracy. Regression analysis indicated that AI-driven transformations in engineering predict improved efficiency ($B=0.449$, $p<0.01$) but a weaker correlation with accuracy ($B=0.234$, p¿0.05). Correlation analysis revealed a moderate positive relationship between perceived efficiency and accuracy ($r=0.571$, $p<0.01$)
Qualitative data supports these findings, with interviewees consistently noting reduced task execution times and reduced errors. One respondent stated, *"AI reduces the mundane, repetitive parts of the job, letting us focus on strategic tasks."* Concerns were expressed over the dependency on the accurate datasets, as one interviewee has stated, *"I only works well when the input data is clean and relevant."*

Challenges in Collaboration

Despite positive impacts on individual tasks, collaboration continues to be a bottleneck. Quantitative data shows lower mean scores for collaboration improvements ($M=3.2$). Interviewees expressed frustrations with the lack of interoperability between AI tools used by different teams. One interviewee stated, *"Each team uses its own tools, and these don't talk to each other."* Resistance to change also appeared as a recurring theme, with interviewees showing concern about a potential loss of autonomy.

Interpretation and Implications

These findings highlighted that although AI significantly enhances operational efficiency and accuracy, its full potential is hindered by collaboration challenges. Addressing these require a dual approach, improving technical interoperability and fostering cultural acceptance within teams.

5.1.2 Support for Customization and Limitations of AI

This theme explores the extent to which AI supports customized requirements and the limitations it encounters in the process. The results highlight the adaptability of AI and its technical and organizational limitations.

Adaptability to Client Needs

Quantitative findings indicate a moderately positive perception of AI's adaptability, with descriptive analysis showing a mean score of 3.5 for "AI as useful in handling client-specific needs". Regression analysis further indicated that adaptability positively predicts perceptions of AI's usefulness ($B=0.389$, $p<0.05$).
Interviewees highlights the ability of AI to automate repetitive customization tasks while maintaining consistency. One interviewee stated, *"I makes it easier to deliver consistent outputs for repetitive customizations."* However, another interviewee said *"Complex, highly tailored requirements still need significant human intervention."*

Limitations in Customization

Qualitative insights revealed multiple limitations, including inflexibility of AI systems when handling unexpected situations. Interviewees regularly expressed concerns about AI's inability to completely replace human judgment in complex designs. One interviewee emphasized, *"For truly customized solutions, we still need experienced engineers to step in."*

Interpretation and Implications

The results indicate that while AI is valuable for standard customization, it has its difficulties with complex, dynamic requirements. Overcoming this limitation will require investing in adaptive AI systems that can learn from unique cases and integrating seamlessly with human expertise.

5.1.3 Time and Cost Savings Through AI

This theme explores the quantifiable benefits that AI provides regarding time and cost efficiencies for both standard and customized tasks. The results show significant cost reductions and process efficiency attribute to AI adaption.

Standard Tasks

Quantitative data highlights significant cost savings in standard tasks, with regression analysis showing a strong correlation between automation and cost reductions ($B=0.521$, $p<0.01$). Descriptive statistics indicate mean scores for time efficiency ($M=3.8$), this reflects participants' appreciations of AI contribution to expediting routine processes.
Qualitative insights further highlight this, with interviewees reporting reductions in repetitive labor. One interviewee stated, *"AI lets us handle routine tasks like network monitoring with minimal effort, saving hours every week."*

Customized Tasks

In customized tasks, quantitative results were less significant, with weaker correlations between AI adoption and cost savings ($r=0.342$, $p<0.05$). Participants recognized AI's capability in reducing customization cycles but also have noted limitations. One interviewee stated, *"AI is helpful for repetitive customizations but doesn't always account for unique client needs."*

Interpretation and Implications

AI offered significant time and costs savings, especially in standard tasks, but its influence on customization remains limited. Future developments should focus on dynamic AI models that are capable of meeting customization requirements.

5.1.4 Technical, Ethical, and Regulatory Challenges

This theme explores the obstacles to AI adoption, ranging from technical to ethical and regulatory challenges. These challenges affect both current practices and the future direction of AI in network engineering.

Technical Challenges

Quantitative data highlighted significant integration challenges, with a mean score of 3.2 for items related to system interoperability. Interviewees highlighted the challenge of integrating AI tools with existing workflows. One interviewee stated *"AI systems often lack the flexibility to integrate with legacy systems, making adoption harder."*

Ethical Challenges

Ethical challenges primarily centered around job displacement and biases in AI algorithms. Qualitative responses indicated concerns about automation replacing human roles, as one interviewee stated *"The fear of losing jobs makes some teams resistant to AI adoption."*

Regulatory Challenges

Quantitative results indicated significant concerns regarding s with frameworks such as GDPR, with a mean score of 3.9. Interviews confirmed this, with interviewees emphasizing the importance of aligning AI practices with evolving regulations. One interviewee stated *"Staying compliant with GDPR adds complexity to every AI implementation."*

Interpretation and Implications

The findings highlighted that although AI possesses transformative potential, it is essential to solve its technical, ethical, and regulatory challenges for sustainable use. Organizations must prioritize transparent AI practices, and robust compliance mechanism.

5.2 Theoretical Contributions

This thesis provides several theoretical contributions to the academic discussion surrounding AI implementation in network engineering and consultancy. These contributions alight with the core research themes and serve to enhance and broaden the existing theories.

Efficiency, Accuracy, and Collaboration in Engineering Task

This research contributes to the understanding of how AI influences efficiency, accuracy, and collaboration in standardized engineering tasks.
Enhancing automation theory, the findings validate the role of AI in improving task efficiency and accuracy, especially through task automation and real-time optimization. Nonetheless, the results also highlight the conditional nature of these benefits, indicating the organizational preparedness and contextual factors significantly moderate AI's impact. This adds to existing automation theories.
AI-human collaboration, by emphasizing the importance of collaboration between AI tools and human engineers, the study emphasizes current theories on AI-driven workflows. The thesis highlights that AI's effectiveness is enhances when combined with human expertise, thus contributing to the evolving discussion on human collaboration.

Support for Customization and Limitations of AI

Hybrid AI-human models, the research presents a conceptual model that combines AI and human expertise to address complex customization tasks. This hybrid approach challenges the perception of AI as a standalone solution, it emphasized its complementary role in handling unique client needs.
Task-specific AI effectiveness, the findings highlight that tasks complexity moderates the utility of AI tools, introducing the concept of task-specific AI effectiveness. This contribution enhances current customization frameworks by integrating the impact of task characteristics on AI performance.

Time and Cost Savings through AI

The research enhances theoretical understanding of AI's economic impact on engineering processes. Diminishing returns in efficiency, the findings challenge the assumption of universal efficiency improvements resulting from AI implementation. The analysis reveals while significant time and cost savings are observed in routine tasks, the study identifies decreasing returns for complex and highly customized tasks. this contribution resource optimization theories by incorporating task-specific constraints. Economic feasibility of AI, the study validates theories on AI-driven resources optimization while also highlighting the limitations of these benefits in scenarios requiring extensive human involvement. This enhances the theoretical discussion on the economic viability of AI.

Technical, Ethical, and Regulatory Challenges

This study enhances the literature on AI adoption by identifying major challenges.
The concept of regulatory readiness as a theoretical construct addresses the challenges associated with adapting to evolving regulatory frameworks, including GDPR and the EU AI Act. This model provides a basis for future studies on regulatory compliance in AI implementation. The findings enhance current ethical adoption frameworks by emphasizing the relationship among organizational readiness, ethical considerations, and compliance requirements. This offers a comprehensive perspective on the challenges of implementing AI responsibly.

Integrated Theoretical Insights

The study's triangulated technique, combining quantitative and qualitative data, provides a balanced perspective that enhances theoretical solidity.
The research demonstrates the importance of combining measurable outcomes with experienced insights, highlighting the importance of integrating both qualitative and quantitative approaches in AI adoption studies. This methodological contribution highlights the necessity for multidimensional frameworks that capture the complex nature of AI integration.

These theoretical contributions validate and expand existing frameworks while introducing new elements and models that enhance the academic comprehension of AI implementation. This study addresses standardized and customized tasks, together with technical, ethical, and regulatory challenges, thereby bridging theoretical gaps and establishing a basis for future research in network engineering and consultancy.

5.3 Practical Implications

This research's findings offer practical insights for network engineering and consultancy, especially for organizations looking to integrate AI technologies efficiently. The practical implications correspond with the study's concepts, providing specific recommendations for enhancing operational efficiency, customization capabilities, and the ethical adoption of AI.

Efficiency, Accuracy, and Collaboration in Engineering Task

AI could automate repetitive engineering tasks, such as network configuration and performance monitoring, so reducing operational challenges and allowing engineers to concentrate on their strategic objectives. Organizations need to invest in AI systems tailored to automate these tasks

while maintaining high level of accuracy.
The research highlights the significance of AI-human collaboration in achieving optimal efficiency. Organizations must educate employees on how to effectively interact with AI systems, creating an environment where AI complements human decision-making instead of substituting it.
The collaboration challenges highlighted in the research can be mitigated using AI-driven technologies that centralize and optimize information sharing. Organizations need to adopt platforms which utilize AI to enhance efficiency in workflows across teams.

Support for Customization and Limitations of AI

While AI excels in standard tasks, its function in customization remains supplementary. Experts need to integrate AI technologies with human expertise to meet complex client-specific requirements, utilizing AI for data-driven insights and repetitive aspects of customization.
The limitations of AI in handling complex customization highlight the need for flexible systems. Organizations should focus on the development or adoption of AI solutions which offer iterative human input, thus guaranteeing adaptability to changing client requirements.
The findings indicate that AI can standardize outputs while preserving the unique aspects of customization. Organizations should strive to standardize simpler tasks while allocating human skills to more complex client requirements.

Time and Cost Savings through AI

AI's capacity to optimize time and cost in routine tasks allows for more resources for more critical operations. Professionals should strategically implement AI in fields with the highest potential for efficiency improvements, such as predictive maintenance and automated monitoring.
Although AI provides significant financial benefits, organizations need to assess the return on investment (ROI) for time savings and cost savings. Decision-makers should conduct cost-benefit assessments to ensure that AI implementation corresponds with their financial goals.
The predictive capabilities of AI in resource allocation may help organizations in preventing both over-provisioning and under-utilization of resources. Organizations should to implement solutions that dynamically adjust to real-time requirements, enhancing operational expenses.

Technical, Ethical, and Regulatory Challenges

Organizations have to tackle challenges related to system integration and data quality. Investments in infrastructure upgrades and data standardization processes can improve the effectiveness of AI approaches.
To address ethical issues, such as job displacement and bias, organizations should establish transparent AI governance guidelines. Involving stakeholders in the ethical development and application of AI tools will foster trust and acceptability among employees.
Compliance to regulations such as GDPR and the EU AI Act is crucial for the sustainable adoption of AI. Organizations should create dedicated groups or positions that oversee regulatory changes and guarantee that AI systems comply to regulations.
Familiarizing staff and management with AI technologies helps facilitate the adoption process. Training programs should emphasize both technical skills and regulatory awareness.

Integrated Practical Insights

The integration of quantitative and qualitative data shows that the success of AI depends on the alignment of technology with organizational readiness, ethical issues, and contextual requirements. This study highlights the importance of a gradual strategy for AI implementation, first with everyday activities and progressively advancing to more complex customized applications.

These practical implications offer a framework for practitioners to capitalize on AI's potential while addressing its limitations. By strategically incorporating AI technologies into processes, organizations can improve operational efficiency, meet client-specific requirements, and cope with the ethical and regulatory challenges of the adoption of AI.

5.4 Study Limitations

This study provides significant insights into the role of AI in network engineering and consultancy, certain limitations must be acknowledged to contextualize its findings. These limitations relate to the methodological and chronological limits of the research process and highlight areas for future research.

Short Time Span

The research was executed within the constrained duration of a master's thesis, from September to December. This limitation affected the scope of the research, including collecting data and analysis. As a result, only one round of data collection was carried out, which could limit the depth of insights and possibilities for iterative refinement.

Limited Sample Size

The research used a relatively sample size, potentially impacting the generalizability of the results. Despite attempts to include various kinds of specialists from the telecommunications industry, a larger sample size would have for better statistical analysis and a greater variety of perspectives, thus enhancing the reliability of the conclusions.

Focus on Self-Reported Data

The research mainly utilized self-reported data collected through surveys and interviews. This method presents possible biases, including social desirability bias, where participants may offer responses they consider favorable rather than accurate. The lack of direct observational or objective evidence to verify these self-reported insights may undermine the reliability of the findings.

Lack of Experimental Validation

The study included quantitative and qualitative analysis but missed experimental validation of AI technologies and their effects on network engineering processes. The absence of controlled testing limits the establishment of causal relationships between AI implementation and observed outcomes. Future research could utilize experimental methods to yield more robust evidence on the effects of AI on efficiency, customization, and related challenges.

These limitations highlight the necessity for caution when generalizing the results of this research. Future research should address these limitations by extending the time frame, expanding the sample size, validating findings through experimental methods, and incorporating more objective data to achieve a more comprehensive understanding of AI's transformative potential in network engineering and consultancy.

Chapter 6

Conclusion and Recommendations

This chapter gives an conclusion of the thesis, this will be done by summarizing the findings, addressing the research questions, and will discuss the broader implications. The findings highlight the potential AI has to enhance efficiency and accuracy in engineering tasks, its limitations in addressing customization, and the challenges related to technical, ethical, and regulatory challenges. At last recommendations for future research are resented, this focuses on opportunities to further advance AI integration and address the identified limitations.

6.1 Conclusion

This research was aimed at investigating the extent to which AI can assist network engineers and consultants in improving efficiency, accuracy and customization in engineering processes. The findings are based on quantitative and qualitative analysis. The four sub-questions were used to tackle the research, the findings of which collectively provide a thorough response to the main research question.

Sub Question 1

How can AI improve the efficiency, accuracy, and collaboration in standard engineering tasks for network consultants and engineers?

AI showed significant potential to enhance efficiency by automating routine tasks, including network configuration, performance monitoring, and fault detection. These capabilities reduce human errors and optimize processes, allowing s to allocate more time to strategic tasks. AI enhances accuracy by validating configurations and utilizing predictive analytics to mitigate potential issues proactively. Collaboration was highlighted as an area where AI tools enhance communication and coordination across teams, however resistance to adoption and isolated teams remain challenges. This support both hypothesis H1a and H1b , in that AI's role in network efficiency positively influences both efficiency and design accuracy.

Sub Question 2

To what extent can AI tools support engineers in addressing customized design requirements, and what limitations do they face in this area?

While AI offers valuable support in customization via predictive modeling and dynamic configurations, its ability to handle highly specific client requirements is limited. Challenges include the need for highly-quality, domain-specific data, computational limitations, and the inability of AI systems to comprehensively interpret complex client needs without substantial human intervention. These findings highlight AI's role as a supportive rather than a standalone tool in customization processes. This partially supports both H3a and H3b that perceived trust moderates the relationship between AI an process efficiency and that perceived trust moderates the relationship between AI and design accuracy.

Sub Question 3

What are the potential time and cost savings from AI implementation in engineering design, both for standard tasks and customized requirements?

The research indicates significant time and cost savings in engineering tasks, attributed to automation, resource optimization, and predictive maintenance. However, these advantages suffer in customized tasks due to the resource intensive nature of customized solutions. The efficiency of AI in identifying bottlenecks and optimizing workflows offers clear economic advantages for routine processes but requires further development to achieve similar outcomes in customization.

Sub Question 4

What challenges, including ethical and regulatory concerns, do network engineers and consultants face when integrating AI into their workflows?

The use of AI into network engineering processes presents significant challenges. Technical issues, including disconnected data systems, lack of standardization, and integration difficulties into existing infrastructures were found. Participants expressed significant ethical concerns, particularly around trust in AI systems and concerns about job displacements. Regulatory challenges, including compliance with the EU AI Act and GDPR, highlight the need for robust governance frameworks and strategic alignment of AI initiatives with legal standards. This supports both H2a and H2b regulatory compliance moderates the relationship between AI and process efficiency and regulatory compliance moderates the relationship between AI and design accuracy.

Research Question

To what extend can Artificial Intelligence (AI) assist network consultants and network engineers in improving the efficiency and accuracy of design and engineering processes in the context of customized requirements?

AI significantly improves efficiency and accuracy in standardized engineering tasks, thus showing its function as an facilitator of automation, predictive maintenance, and resource optimization. However, its utilization in customized requirements remain limited due to the underlying complexity of client-specific solutions and its dependence on human expertise. Despite these challenges, AI holds significant promise as a supportive tool, which is capable op optimizing workflows and improving consistency when utilized along with human intervention.

In conclusion this thesis highlights transformative capacity of AI in network and consultancy, showing its potential to significantly enhance efficiency and accuracy in engineering tasks. AI has shown its efficiency as a valuable tool for reducing human labor, minimizing errors and optimizing processes through automation, predictive maintenance, and resource management. These enhancements allow engineers to focus on higher-value, strategic responsibilities while simultaneously enhancing operational agility and productivity.

However, the research highlight that the integration of AI in customized design requirements show significant challenges. Although AI tools present promising capabilities such as dynamic configurations and predictive modeling, their effectiveness is limited by the complexity of client-specific requirements and the necessity for high-quality, domain-specific data. This emphasizes the need for human expertise to interpret complex requirements, validate AI outputs, and ensure alignment with client expectations. The role that AI has in personalization is currently more complementary rather than independent, requiring additional advancements to fully address its limitations.

The study identifies significant obstacles to to AI adoption, including disconnected data systems, ethical concerns such as job displacement, and regulatory challenges presented by frameworks such as GDPR and EU AI Act. These challenges highlight the need for robust governance mechanisms and compliance frameworks in order to guarantee successful AI implementation which is responsible and effective. Addressing these challenges will be essential for organizations aiming to fully unlock the potential of AI in network engineering and consultancy.

While AI offers significant benefits for standard tasks, its application in customization and its wider adaption requires additional refinement and advancement. Future research and innovation could focus on enhancing AI's adaptability, improving data integrations and fostering trust among engineers and stakeholders. By overcoming these challenges, organizations can leverage AI's potential more effectively, driving innovation, reducing costs, and achieving operational excellence in network engineering and consultancy.

6.2 Recommendations for Future Research

This research has identified key areas where AI can improve network engineering and consultancy, while also highlighting its current limitations. Future research could focus on the following, evolving roles of network engineers and consultants; adapting AI for customized design requirements; human-AI collaboration models; experimentally validating AI benefits.

Evolving Roles of Network Engineers and Consultants

As AI continues to automate standard tasks and enhance decision-making processes, the roles or network engineers and consultants are likely to shift toward more strategic, supervisory, and innovative positions. Future research should look at how these roles evolve over time, focusing on the new skill sets required. the influence on professional identity and the balance between human expertise and the capabilities of AI. Long term research in this area could provide significant insights for workforce development and educational programs.

Adapting AI for Customized Design Requirements

Addressing client specific requirements remains a significant challenge for AI systems. Future research could focus on developing adaptive AI models which are capable of handing the complexity of customized design requirements. This could involve creating algorithms which integrate domain specific knowledge, utilizing advanced learning techniques, and improving the how the outputs of AI are interpreted. These advancements could bridge the cap between the potential of AI and its practical application within customization.

Human-AI Collaboration Models

Understanding the dynamics of human-AI interaction is essential for optimizing the effectiveness of AI tools. Future research should explore how engineers and consultants work with AI systems, with a focus on factors such as trust, acceptance, and the perceived usefulness of these tools. Research may also examine how to optimize processes and AI capabilities to achieve the best results.

Experimentally Validating AI Benefits

This study has provided AI's potential benefits through qualitative quantitative analysis, experimental research could further validate these findings. Controlled experiments which assess AI tools in real-world engineering tasks could provide concrete dat on their impact on efficiency, accuracy, and customization. these experiments could also help refine theoretical models of AI adoption and identify areas requiring significant improvements.

Bibliography

Alpaydin, E. (2020). *Introduction to machine learning* (Fourth edition). The MIT Press.

Bajpai, M. (2023). The Transformative Impact of AI Ops/ML and Observability in Automating Networking Operations and Network Security. https://doi.org/10.5281/ZENODO.14208771

Balaram, G., & Prabhu, S. (2023). 5G Network Management Framework for Improved Customer Experience using Artificial Intelligence and Big data. *2023 4th International Conference for Emerging Technology (INCET)*, 1–6. https://doi.org/10.1109/INCET57972.2023.10170728

Balmer, R. E., Levin, S. L., & Schmidt, S. (2020). Artificial Intelligence Applications in Telecommunications and other network industries [Publisher: Elsevier BV]. *Telecommunications Policy*, *44*(6), 101977. https://doi.org/10.1016/j.telpol.2020.101977

Bhattacharyya, D. K., & Kalita, J. K. (2014). *Network anomaly detection: A machine learning perspective*. CRC Press.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., . . . Amodei, D. (2020, July). Language Models are Few-Shot Learners [arXiv:2005.14165 [cs]]. https://doi.org/10.48550/arXiv.2005.14165

Caesar, J. (2024, December). What Is Quality of Service (QoS)? Network Priority Explained. https://techreviewadvisor.com/what-is-quality-of-service-qos/

Cath, C. (2018). Governing artificial intelligence: Ethical, legal and technical opportunities and challenges. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *376*(2133), 20180080. https://doi.org/10.1098/rsta.2018.0080

Chen, J., Storchan, V., & Kurshan, E. (2021). Beyond Fairness Metrics: Roadblocks and Challenges for Ethical AI in Practice. https://doi.org/10.48550/ARXIV.2108.06217

Cisco. (2024). What Is Artificial Intelligence in Networking? https://www.cisco.com/c/en/us/solutions/artificial-intelligence/artificial-intelligence-machine-learning-in-networking.html

Creswell, J. W. (1999). Mixed-Method Research: Introduction and Application.

Cui, Q., You, X., Wei, N., Nan, G., Zhang, X., Zhang, J., Lyu, X., Ai, M., Tao, X., Feng, Z., Zhang, P., Wu, Q., Tao, M., Huang, Y., Huang, C., Liu, G., Peng, C., Pan, Z., Sun, T., . . . Yuen, C. (2024). Overview of AI and Communication for 6G Network: Fundamentals, Challenges, and Future Research Opportunities [Version Number: 2]. https://doi.org/10.48550/ARXIV.2412.14538

Du, H., Liu, G., Lin, Y., Niyato, D., Kang, J., Xiong, Z., & Kim, D. I. (2024). Mixture of Experts for Intelligent Networks: A Large Language Model-enabled Approach. *2024 International Wireless Communications and Mobile Computing (IWCMC)*, 531–536. https://doi.org/10.1109/IWCMC61514.2024.10592370

Eberding, L. M. (2020). Task-environments for evaluating learning and autonomy in AI architectures. Retrieved December 19, 2024, from https://www.semanticscholar.org/paper/Task-environments-for-evaluating-learning-and-in-AI-Eberding/641e4c1801e9f833e57fd11e8156de1f25e59b69

European Commission. (2024). AI Pact — Shaping Europe's digital future. Retrieved November 27, 2024, from https://digital-strategy.ec.europa.eu/en/policies/ai-pact

Folorunsho, S. O., Adenekan, O. A., Ezeigweneme, C., Somadina, I. C., & Okeleke, P. A. (2024). Optimizing network performance and quality of service with AI-driven solutions for future telecommunications. *International Journal of Frontiers in Engineering and Technology Research*, *7*(1), 073–092. https://doi.org/10.53294/ijfetr.2024.7.1.0041

Fontana, A., & Frey, J. (2000). The Interview: From Structured Questions to Negotiated Text. Retrieved November 25, 2024, from https://www.semanticscholar.org/paper/The-Interview%3A-From-Structured-Questions-to-Text-Fontana-Frey/7d8afab47fe14706f54d87c801de2e4a93ca9c30

Girasa, R. (2020). AI as a Disruptive Technology. In *Artificial Intelligence as a Disruptive Technology* (pp. 3–21). Springer International Publishing. https://doi.org/10.1007/978-3-030-35975-1_1

Gomez-Carmona, O., Casado-Mansilla, D., Lopez-de-Ipina, D., & Garcia-Zubia, J. (2022). Optimizing Computational Resources for Edge Intelligence Through Model Cascade Strategies. *IEEE Internet of Things Journal*, *9*(10), 7404–7417. https://doi.org/10.1109/JIOT.2021.3118845

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative Adversarial Networks [Version Number: 1]. https://doi.org/10.48550/ARXIV.1406.2661

Goodman, B., & Flaxman, S. (2017). European Union regulations on algorithmic decision-making and a "right to explanation" [arXiv:1606.08813 [stat]]. *AI Magazine*, *38*(3), 50–57. https://doi.org/10.1609/aimag.v38i3.2741

Grace, K., Stewart, H., Sandkühler, J. F., Thomas, S., Weinstein-Raun, B., & Brauner, J. (2024). Thousands of AI Authors on the Future of AI. https://doi.org/10.48550/ARXIV.2401.02843

Guest, G., Bunce, A., & Johnson, L. (2006). How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Hernandez, D., & Brown, T. (2020). Measuring the Algorithmic Efficiency of Neural Networks.

Huang, C., Zhang, Z., Mao, B., & Yao, X. (2023). An Overview of Artificial Intelligence Ethics. *IEEE Transactions on Artificial Intelligence*, *4*(4), 799–819. https://doi.org/10.1109/TAI.2022.3194503

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service [Publisher: SAGE Publications]. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Ismanov, I., Qayumov, N., Mukhamadjonova, D., & Akhmadaliyev, B. (2024). AI and Cost Management: Strategies for Reducing Expenses and Improving Profit Margins in Business. *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, 1–7. https://doi.org/10.1109/ICKECS61492.2024.10616761

Komaragiri, V. B., & Edward, A. (2022). AI-Driven Vulnerability Management and Automated Threat Mitigation. *International Journal of Scientific Research and Management (IJSRM)*, *10*(10), 980–998. https://doi.org/10.18535/ijsrm/v10i10.ec05

KPN. (2023). KPN CMD 2023 Press release. https://s202.q4cdn.com/886546970/files/doc_news/2023/11/06/231107-KPN-announces-Connect-Activate-Grow-strategy.pdf

KPN. (2024). KPN in een oogopslag. Retrieved August 6, 2024, from https://www.overons.kpn/nl/het-bedrijf/kpn-in-een-oogopslag

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, *60*(6), 84–90. https://doi.org/10.1145/3065386

Kulkarni, U., Meena, S. M., Gurlahosur, S. V., Benagi, P., Kashyap, A., Ansari, A., & Karnam, V. (2021). AI Model Compression for Edge Devices Using Optimization Techniques [Series Title: Studies in Computational Intelligence]. In V. K. Gunjan & J. M. Zurada (Eds.), *Modern Approaches in Machine Learning and Cognitive Science: A Walkthrough* (pp. 227–240, Vol. 956). Springer International Publishing. https://doi.org/10.1007/978-3-030-68291-0_17

Kumar. (2024, February). Top 15 Challenges of Artificial Intelligence in 2025. Retrieved November 27, 2024, from https://www.simplilearn.com/challenges-of-artificial-intelligence-article

Leitão, P., & Karnouskos, S. (2015). *Industrial Agents*. Elsevier. https://doi.org/10.1016/C2013-0-15269-5

Luntovskyy, A. (2024). How AI Meets Networking and Networks Meet AI Applications. In A. Luntovskyy, M. Klymash, I. Melnyk, M. Beshley, & A. Schill (Eds.), *Digital Ecosystems: Interconnecting Advanced Networks with AI Applications* (pp. 56–80, Vol. 1198). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-61221-3_4

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2019). A Survey on Bias and Fairness in Machine Learning. https://doi.org/10.48550/ARXIV.1908.09635

Moro-Visconti, R. (2024). Artificial Intelligence-Driven Industry Applications. In *Artificial Intelligence Valuation* (pp. 613–641). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-53622-9_10

Muller, C., Magill, E., Prosser, P., & Smith, D. (1993). Artificial intelligence in telecommunications. *Proceedings of GLOBECOM '93. IEEE Global Telecommunications Conference*, *9*, 883–887. https://doi.org/10.1109/glocom.1993.318205

Nguyen-Duc, A., Cabrero-Daniel, B., Przybylek, A., Arora, C., Khanna, D., Herda, T., Rafiq, U., Melegati, J., Guerra, E., Kemell, K.-K., Saari, M., Zhang, Z., Le, H., Quan, T., & Abrahamsson, P. (2023, October). Generative Artificial Intelligence for Software Engineering – A Research Agenda [arXiv:2310.18648 [cs]]. Retrieved July 24, 2024, from http://arxiv.org/abs/2310.18648

Nilsson, N. J. (1998). *Artificial Intelligence: A New Synthesis*. Morgan Kaufmann.

Nnamani, C. C. (2024). Exploiting AI Capabilities: An in-Depth Analysis of Artificial Intelligence Integration in Cybersecurity for Threat Detection and Response. *International Journal of Education, Management, and Technology*, *2*(3), 268–286. https://doi.org/10.58578/ijemt.v2i3.3904

Nti, I. K., Adekoya, A. F., Weyori, B. A., & Nyarko-Boateng, O. (2022). Applications of artificial intelligence in engineering and manufacturing: A systematic review [Publisher: Springer Science and Business Media LLC]. *Journal of Intelligent Manufacturing*, *33*(6), 1581–1601. https://doi.org/10.1007/s10845-021-01771-6

Oduri, S. (2019). Future-Proofing Cloud Networks with AI and Security Engineering. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *9*(2), 794–800. https://doi.org/10.61841/turcomat.v9i2.14736

Olabanji, S. O., Marquis, Y. A., Adigwe, C. S., Ajayi, S. A., Oladoyinbo, T. O., & Olaniyi, O. O. (2024). AI-Driven Cloud Security: Examining the Impact of User Behavior Analysis on Threat Detection. *Asian Journal of Research in Computer Science*, *17*(3), 57–74. https://doi.org/10.9734/ajrcos/2024/v17i3424

Salehi, H., & Burgueño, R. (2018). Emerging artificial intelligence methods in structural engineering. *Engineering Structures*, *171*, 170–189. https://doi.org/10.1016/j.engstruct.2018.05.084

Sheikh, H., Prins, C., & Schrijvers, E. (2023). Artificial Intelligence: Definition and Background. In H. Sheikh, C. Prins, & E. Schrijvers (Eds.), *Mission AI: The New System Technology* (pp. 15–41). Springer International Publishing. https://doi.org/10.1007/978-3-031-21448-6_2

Taherdoost, H. (2016). Sampling Methods in Research Methodology; How to Choose a Sampling Technique for Research. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3205035

Teletimes International. (2024). How is AI Transforming Predictive Maintenance in Telecom Networks. https://teletimesinternational.com/2024/ai-transforming-predictive-maintenance-telecoms/

Turing, A. M. (1950). I.—COMPUTING MACHINERY AND INTELLIGENCE. *Mind*, *59*(236), 433–460. https://doi.org/10.1093/mind/LIX.236.433

Umoga, U. J., Sodiya, E. O., Ugwuanyi, E. D., Jacks, B. S., Lottu, O. A., Daraojimba, O. D., & Obaigbena, A. (2024). Exploring the potential of AI-driven optimization in enhancing network performance and efficiency. *Magna Scientia Advanced Research and Reviews*, *10*(1), 368–378. https://doi.org/10.30574/msarr.2024.10.1.0028

Van Stein, N., De Winter, R., Bäck, T., & Kononova, A. V. (2023). AI for Expensive Optimization Problems in Industry. *2023 IEEE Conference on Artificial Intelligence (CAI)*, 251–254. https://doi.org/10.1109/CAI54212.2023.00113

Vemuri, N., Thaneeru, N., & Manoj Tatikonda, V. (2022). AI-Driven Predictive Maintenance in the Telecommunications Industry. *Journal of Science & Technology*, *3*(2), 21–45. https://doi.org/10.55662/JST.2022.3201

Venkataram, P. (1997). Artificial intelligence approaches to network management: Recent advances and a survey. *Computer Communications*. Retrieved December 9, 2024, from https://www.academia.edu/71560477/Artificial_intelligence_approaches_to_network_management_recent_advances_and_a_survey

Voigt, P., & Von Dem Bussche, A. (2017). *The EU General Data Protection Regulation (GDPR)*. Springer International Publishing. https://doi.org/10.1007/978-3-319-57959-7

Welsh, R. (2019). Defining Artificial Intelligence. *SMPTE Motion Imaging Journal*, *128*(1), 26–32. https://doi.org/10.5594/JMI.2018.2880366

Wiese, T. L. (2024). Predictive Maintenance Using Artificial Intelligence in Critical Infrastructure: A Decision-Making Framework. *International Journal of Engineering, Business and Management*, *8*(4), 01–04. https://doi.org/10.22161/ijebm.8.4.1

Yadav, M. K., Gaurav, A., & Kumar, S. (2023). AI-Powered Networking: Unlocking Efficiency and Performance. *International Journal of Research Publication and Reviews*, *4*(8), 1210–1217. https://ijrpr.com/uploads/V4ISSUE8/IJRPR16187.pdf

Zhang, G., Raina, A., Cagan, J., & McComb, C. (2021). A cautionary tale about the impact of AI on human design teams. *Design Studies*, *72*, 100990. https://doi.org/10.1016/j.destud.2021.100990

Zhao, W., Olshefski, D., & Schulzrinne, H. (2024). Internet Quality of Service: An Overview.

Appendix A

Survey Design

Table A.1: Survey Design

Section	Question	Answer Type
Background and Experience		
What is your current role?	• Network Engineer • Network Consultant • IT Manager or Network Operations Manager • Cybersecurity Specialist • Data Scientist or AI Specialist • System Administrator or Infrastructure Engineer • Project Manager • Technical Support Engineer • Other (please specify)	Single-Choice
How many years of experience do you have in network engineering or consulting?	• Less than 1 year • 1-3 years • 4-6 years • 7-10 years • More than 10 years	Single-Choice

What is your highest level of education?	• High school diploma • MBO • HBO/WO Bachelor's degree • HBO Master's degree • WO Master's degree • Doctoral degree (PhD) • Other (please specify)	Single-Choice
In what industry does your organization primarily operate?	• Telecommunications • IT Services • Financial Services • Healthcare • Government • Other (please specify)	Single-Choice
How many employees does your organization have?	• 1-50 • 51-200 • 201-500 • 501-1000 • More than 1000	Single-Choice
Perception of AI in Network Engineering		
How familiar are you with the concept of AI in network engineering?	Likert Scale (Not familiar at all to Extremely familiar)	Likert Scale
To what extent do you believe AI can improve the efficiency of network engineering tasks?	Likert Scale (Not at all to To a very large extent)	Likert Scale
To what extent do you believe AI can improve the accuracy of network engineering tasks?	Likert Scale (Not at all to To a very large extent)	Likert Scale
How strongly do you agree with the statement: ÄI can fundamentally transform network engineering and consultancy"?	Likert Scale (Strongly disagree to Strongly agree)	Likert Scale
To what extent do you believe AI could enhance collaboration between network engineers and consultants?	Likert Scale (Not at all to To a very large extent)	Likert Scale
AI for Efficiency and Time-Saving		

Which tasks do you think AI could improve in terms of time efficiency?	• Network monitoring and troubleshooting • Device configuration • Network traffic analysis • Predictive maintenance • None of the above	Multi-Choice
How likely are you to use AI tools if they reduce the time needed to perform routine tasks?	Likert Scale (Extremely unlikely to Extremely likely)	Likert Scale
AI for Accuracy and Error Reduction		
In your opinion, how effective would AI be in reducing human errors in network engineering?	Likert Scale (Not effective at all to Extremely effective)	Likert Scale
How comfortable would you be relying on AI to make recommendations in complex, customized network setups?	Likert Scale (Extremely uncomfortable to Extremely comfortable)	Likert Scale
Customization and Adaptability		
How adaptable do you think AI currently is in handling unique, client-specific network requirements?	Likert Scale (Not adaptable to Extremely adaptable)	Likert Scale
Would you consider AI a useful tool to help manage and customize solutions for clients' specific needs?	Likert Scale (Strongly disagree to Strongly agree)	Likert Scale
Potential Challenges with AI Integration		
What are your main concerns with integrating AI in network engineering?	• Security and data privacy risks • Lack of trust in AI's accuracy • High implementation costs • Lack of understanding of AI technology • None of the above	Multi-Choice
How challenging do you think it would be to integrate AI into your current workflow?	Likert Scale (Not challenging at all to Extremely challenging)	Likert Scale
Anticipated Impact on Job Satisfaction and Role Changes		
Do you think that AI adoption would make your job easier or more challenging?	Much easier Somewhat easier No change Somewhat more challenging Much more challenging	Single-Choice
How likely are you to adopt AI tools in your work if they improve accuracy and efficiency?	Likert Scale (Extremely unlikely to Extremely likely)	Likert Scale

Future of AI in Network Engineering		
To what extent do you believe AI will play a role in network engineering and consultancy in the future?	Likert Scale (Not at all to To a very large extent)	Likert Scale
What additional resources would you find helpful for AI adoption?	• Training on AI tools and techniques • Case studies or examples of AI in network engineering • Support from AI consultants • Increased data security measures • None of the above	Multi-Choice
Attitude and Usage Intentions		
Which of the following best describes your current view of AI in network engineering?	• AI is essential for future advancements • AI is useful but not essential • AI has limited applicability • AI is unnecessary or not relevant	Single-Choice
How interested are you in receiving training on AI tools for network engineering?	Likert Scale (Not interested to Extremely interested)	Likert Scale
Do you feel that your organization is prepared to support AI integration?	Likert Scale (Strongly disagree to Strongly agree)	Likert Scale
Open-Ended Questions		
What are your primary expectations from AI in network engineering?	Open text	Open-Ended
Are there specific concerns you have about the impact of AI on your job?	Open text	Open-Ended

Appendix B

Interviews

This appendix shows the summaries for each question. Each summary shows the responses and perspectives gathered from all the twelve interviews per question, offering a overview of their insight on AI in network engineering. AI has been used to summarize the interviews

Table B.1: Summary of Key Insights on Technical, Ethical, and Regulatory Challenges in AI Integration

Question 1: How would you describe the current efficiency and accuracy in your standard engineering tasks?
Participants expressed mixed perspectives regarding the current efficiency and accuracy in standard engineering tasks. Many highlighted inefficiencies stemming from redundant workflows, manual processes, and poor data quality. One participant noted that templates used for network configurations are often outdated and reused without proper validation, resulting in recurring errors. Another emphasized that reliance on manual processes not only slows down tasks but also increases the likelihood of mistakes, particularly during transitions between teams. Several respondents rated the overall efficiency and accuracy of their tasks as suboptimal, citing fragmented workflows and a lack of standardized processes as key barriers. One interviewee explained that the fragmented nature of current workflows often leads to delays and miscommunication, thereby reducing overall productivity. Another pointed out that while automation is helpful in some areas, its effectiveness is heavily dependent on the quality of the initial data, which often fails to meet the required standards. There was consensus that manual tasks, such as configuration and monitoring, take considerable time and are prone to human error. Some participants emphasized the need for better validation processes to reduce errors and streamline workflows. Automation and AI were frequently mentioned as potential solutions to address these challenges, particularly for ensuring consistency and minimizing the impact of poor input data.
Question 2: What collaboration challenges do you experience when performing these tasks?

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Table B.1: Summary of Key Insights on Technical, Ethical, and Regulatory Challenges in AI Integration (Continued)

Participants shared a range of collaboration challenges that impact the efficiency and effectiveness of their workflows. A recurring theme was the lack of effective communication and coordination among teams. One participant noted, *"Different teams often work in silos, which leads to poor information sharing and delays when projects require cross-team collaboration."* Another echoed this sentiment, emphasizing that *"Misalignment between management and operational teams causes confusion about priorities and expectations."* Several participants highlighted challenges in securing buy-in for data-driven approaches. As one explained, *"There's resistance to adopting new, AI-driven methods because some team members prefer sticking to familiar processes."* This resistance not only slows down the adoption of innovative tools but also limits the potential for collaborative problem-solving. Interdependencies between teams were also a significant challenge. One respondent pointed out that *"When one team is delayed, it creates a bottleneck for others, making it difficult to meet deadlines."* Another added, *"Handoffs between teams are often incomplete or lack clarity, which leads to rework and errors."* A few participants noted that tools designed to facilitate collaboration are often underutilized or poorly integrated into workflows. As one mentioned, *"We have systems in place to share updates and coordinate tasks, but not everyone uses them effectively."*
Question 3: How do you think AI can play a role in improving efficiency, accuracy, and collaboration within these tasks?
Participants expressed optimism about the potential of AI to enhance efficiency, accuracy, and collaboration in engineering tasks. Many highlighted the role of AI in automating routine processes and minimizing errors. One participant explained, *"AI can handle repetitive tasks like configuration far faster and with more consistency than humans, reducing time and errors."* Another noted, *"With machine learning models, AI can detect patterns in data that humans might miss, leading to more accurate insights and better decision-making."* In terms of collaboration, several participants emphasized AI's ability to integrate and streamline communication between teams. As one shared, *"AI-powered tools can provide centralized platforms for sharing updates and aligning team objectives, which can reduce misunderstandings and delays."* Another explained, *"AI can help facilitate cross-team workflows by identifying bottlenecks and suggesting ways to optimize processes."* Predictive capabilities were frequently mentioned as a key advantage. One participant remarked, *"AI's ability to predict issues before they arise ensures teams can focus on solving problems proactively rather than reactively."* This sentiment was echoed by another, who said, *"By analyzing historical data, AI can provide actionable recommendations that improve both efficiency and collaboration."* However, participants also noted that the effectiveness of AI depends on proper implementation and the quality of the input data. One explained, *"AI tools are only as good as the data you feed them. Without accurate input, the outputs will also be flawed."*
Question 4: How often do you encounter situations where specific client requirements demand customization?

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Table B.1: Summary of Key Insights on Technical, Ethical, and Regulatory Challenges in AI Integration (Continued)

Participants consistently reported that customization is a frequent and essential part of their work due to the diverse needs of clients. One participant stated, *"Most enterprise clients have unique requirements that cannot be addressed with standard solutions."* Another explained, *"Customization is almost always necessary because no two networks are the same, especially when dealing with large-scale clients."* While some participants noted an effort to standardize processes wherever possible, they acknowledged that client-specific demands often necessitate deviations. One participant shared, *"We try to use standard modules as a base, but customization is inevitable for meeting specific objectives."* Another emphasized, *"Even clients who request standard setups end up needing adjustments to meet their operational constraints."* In highly specialized projects, customization becomes even more critical. One interviewee remarked, *"Enterprise-level clients demand solutions tailored to their infrastructure, which often requires us to go far beyond standard offerings."* Another added, *"We frequently deal with requests for custom integrations and configurations that align with the client's existing systems."* These responses underline that while efforts to standardize are ongoing, the need for customization remains a dominant aspect of engineering tasks due to the highly specific and varied requirements of clients.
Question 5: What limitations do you currently experience when using AI to support customization?
Participants identified several limitations in the ability of AI to fully support customization tasks. A recurring issue was AI's lack of flexibility in adapting to highly specific client requirements. One participant noted, *"AI tools are often built for standard tasks, and they struggle when faced with unique scenarios that fall outside their training data."* Another shared, *"Customization frequently requires nuanced decision-making that AI cannot yet replicate."* The quality of input data was also highlighted as a critical limitation. One respondent explained, *"AI's effectiveness is entirely dependent on the data it's given, and when the data is incomplete or inaccurate, it leads to subpar results."* Another added, *"For highly customized tasks, gathering the right data for AI training is often a significant challenge."* Participants also pointed out the high level of manual intervention required when AI tools fail to meet customization needs. One interviewee remarked, *"Even when we use AI, a lot of manual adjustments are still needed to meet the specific demands of our clients."* This issue was exacerbated by the limited ability of AI tools to integrate seamlessly with existing systems. *"Integrating AI into legacy systems for customization is extremely complex and time-consuming,"* shared another participant. Some respondents highlighted the resource-intensive nature of customizing AI models. One stated, "*Training AI for specific use cases takes a lot of time and expertise, and the cost can outweigh the benefits for smaller projects."*
Question 6: To what extent do you think AI could help more effectively support these customization requirements?

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Table B.1: Summary of Key Insights on Technical, Ethical, and Regulatory Challenges in AI Integration (Continued)

Participants expressed cautious optimism about AI's potential to support customization more effectively. One participant explained, *"AI can significantly speed up customization by automating repetitive aspects of the process, like generating initial configurations or testing scenarios."* Another noted, "With better data and improved algorithms, AI could handle many standard customization tasks, reducing the workload for engineers." However, participants consistently emphasized the need for AI to evolve to meet more complex and nuanced requirements. As one stated, *"AI is currently helpful for basic or semi-standard customization, but it still struggles with highly specific demands that require contextual understanding."* Another participant added, *"AI could better support customization if it were able to learn continuously from past projects and adapt dynamically to client-specific needs."* The use of AI for predictive analytics and scenario simulation was highlighted as a key area for improvement. One respondent remarked, *"AI's ability to simulate different configurations and predict their outcomes is already useful, but with further development, it could become a real game-changer for handling customization."* Despite these possibilities, challenges remain. Some participants noted that *"AI's potential will always be limited by the quality of the data and the ability to train it for highly specific use cases."* Others suggested that human oversight will remain essential for ensuring that customization aligns with client expectations, even as AI capabilities expand.
Question 7: What potential time and cost savings do you think AI could bring to standard engineering tasks?
Participants were optimistic about the potential of AI to deliver significant time and cost savings in standard engineering tasks. One participant noted, *"AI can reduce the time spent on repetitive processes like configuration and monitoring, which currently take up a large portion of our workload."* Another emphasized, *"By automating these tasks, we not only save time but also reduce the costs associated with human errors and the need for rework."* Automation of routine tasks was a central theme. One respondent shared, *"With tools like machine learning, AI can streamline tasks such as performance monitoring and fault detection, which would otherwise require significant manual effort."* Another highlighted resource optimization, stating, *"AI can dynamically allocate resources like bandwidth, ensuring efficiency and preventing over-provisioning, which saves costs."* Participants also mentioned predictive maintenance as a key area where AI can save time and costs. *"AI can predict when equipment is likely to fail, allowing us to perform maintenance proactively and avoid costly downtime,"* explained one respondent. Another added, *"By reducing the need for reactive troubleshooting, we save not only time but also the operational costs associated with system disruptions."* However, participants noted that these savings are contingent on proper implementation. One explained, *"The cost savings AI promises can only be realized if the systems are set up correctly and if the quality of input data is high."*
Question 8: Do you think AI could also provide benefits in terms of cost savings for customization requirements? If so, how?

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Table B.1: Summary of Key Insights on Technical, Ethical, and Regulatory Challenges in AI Integration (Continued)

Participants expressed cautious optimism about AI's ability to provide cost savings in customization tasks, noting specific areas where AI could reduce costs. One participant stated, *"AI can help streamline the customization process by generating initial configurations, reducing the time engineers need to spend on repetitive adjustments."* Another emphasized, *"By simulating different scenarios, AI can help avoid costly trial-and-error processes."* Predictive analytics was frequently mentioned as a key cost-saving capability. *"AI can predict the resources needed for a specific customization task, which helps prevent over-provisioning or under-utilization,"* explained one respondent. Another added, *"Predictive tools can anticipate issues early, reducing the need for expensive revisions during implementation."* However, some participants highlighted limitations in AI's current capabilities for highly customized requirements. One shared, *"AI still struggles with handling unique and highly specific client needs, so manual intervention is often required, which adds to the cost."* Another noted, *"While AI can reduce costs for standard customizations, the setup and training for highly specialized tasks can be resource-intensive."* Despite these limitations, participants agreed that as AI evolves, its ability to provide cost savings in customization will improve. One respondent suggested, "*With better integration and continuous learning, AI could eventually reduce the overhead costs associated with complex customizations.*"
Question 9: What technical, ethical, or regulatory challenges do you experience when integrating AI into your work?
Technical A recurring theme was the lack of standardization and interoperability in AI tools. One participant remarked, *"AI systems are difficult to integrate with existing workflows because there's no standard framework for implementation."* Another highlighted data quality issues, stating, *"AI tools rely heavily on clean, structured data, but our data is often incomplete or inconsistent."* Legacy systems were also identified as a challenge, with one respondent explaining, *"Integrating AI into older systems is time-consuming and resource-intensive."* **Ethical**Concerns about job displacement and transparency in AI decision-making were frequently mentioned. One participant shared, *"There's a fear among engineers that AI could replace their roles, even though it's meant to assist rather than replace."* Another emphasized the importance of trust, noting, *"AI decisions aren't always transparent, which makes it hard for teams to fully rely on them."* **Regulatory** Navigating evolving regulatory frameworks, such as GDPR and the EU AI Act, was a major concern. One participant noted, *"AI implementation is challenging because the rules are constantly changing, and compliance requires significant effort."* Another added, *"Meeting the transparency and accountability standards set by the EU AI Act adds complexity to our workflows."* Participants also highlighted the absence of clear liability frameworks for AI errors. As one explained, *"When an AI system makes a mistake, it's unclear who is responsible—the developers, the users, or the organization implementing it."*
Question 10: How do you think these challenges could influence the future use of AI?

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Table B.1: Summary of Key Insights on Technical, Ethical, and Regulatory Challenges in AI Integration (Continued)

Participants highlighted how technical, ethical, and regulatory challenges could shape the future adoption and application of AI in their field. Many emphasized that addressing these challenges is critical to ensuring the successful and widespread use of AI. **Technical** Technical limitations, particularly related to data quality and system interoperability, were seen as significant barriers to progress. One participant explained, *"If data quality issues aren't resolved, AI systems will remain unreliable and their potential impact will be limited."* Another noted, *"The lack of standardization makes it harder to scale AI solutions, which could slow adoption in larger organizations."* **Ethical**Participants expressed concerns about workforce acceptance of AI due to job displacement fears. One remarked, *"If AI is perceived as a threat to jobs, there will be resistance to its implementation, which could hinder its growth."* Another emphasized the importance of trust, stating, *"Without transparent AI systems, users won't fully rely on them, and adoption will stagnate."* **Regulatory**Regulatory frameworks like GDPR and the EU AI Act were seen as both a challenge and an opportunity. One participant shared, *"These regulations could slow down implementation in the short term, but they are essential for building trust and ensuring ethical use in the long run."* Another added, *"Clearer accountability frameworks will encourage more organizations to adopt AI confidently."* **Opportunities for growth** Despite these challenges, participants identified opportunities for growth if these barriers are addressed. One suggested, *"If AI tools evolve to address data issues and become more transparent, they could revolutionize how we work."* Another remarked, *"Overcoming regulatory challenges will not only enable broader adoption but also ensure that AI is implemented in a way that is ethical and sustainable."*

Appendix C

Detailed Results for Efficiency and Accuracy

C.1 Model Summary for Efficiency and Accuracy

Table C.1: Model Summary for Efficiency and Accuracy

Model	**R**	**R-Squared**	**Adjusted R-Squared**
Efficiency (Q8)	0.449	0.201	0.173
Accuracy (Q9)	0.234	0.055	0.019

C.2 ANOVA Results for Efficiency and Accuracy

Table C.2: ANOVA Results for Efficiency and Accuracy

Dependent Variable	**F**	**df**	**p**
ImproveEfficiency (Q8)	7.054	(1, 28)	0.013*
ImproveAccuracy (Q9)	1.617	(1, 28)	0.214

*p 0.05

Appendix D

Detailed Results for Customization and Limitations

D.1 Descriptive Statistics for Customization and Limitations of AI

Table D.1: Descriptive Statistics for Customization and Limitations of AI

Variable	**Mean**	**Std. Deviation**	**Min**	**Max**
AdaptabilityToClientNeeds (Q15)	3.89	0.547	3	5
RoleOfFamiliarityAndTrust (Q16)	3.75	0.512	2	5
ExperienceLevelsCustomization (Q17)	3.65	0.601	2	5

D.2 Correlation Matrix for Customization and Limitations of AI

Table D.2: Correlation Matrix for Customization and Limitations of AI

Variable	**Mean**	**Std. Deviation**	**Min**	**Max**
AdaptabilityToClientNeeds (Q15)	3.89	0.547	3	5
RoleOfFamiliarityAndTrust (Q16)	3.75	0.512	2	5
ExperienceLevelsCustomization (Q17)	3.65	0.601	2	5

D.3 Regression Coefficients for Customization and Limitations of AI

Table D.3: Regression Coefficients for Customization and Limitations of AI

Dependent Variable	**Predictor**	**B**	**Beta**	**t**	**p**
AdaptabilityToClientNeeds (Q15)	FamiliarityAndTrust (Q16)	0.472	0.472	3.214	0.002**
ExperienceLevelsCustomization (Q17)	FamiliarityAndTrust (Q16)	0.541	0.541	3.781	0.001**

$^{**}p < 0.01$