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Syed Hussain Murtaza

Socio-Economic Impact of Generative AI on Workforce Transformation

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Author: Syed Hussain Murtaza
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ABSTRACT:

Generative Artificial Intelligence development is changing the way work processes, decision-making, and communication processes in different industries are structured. In operations and administration, Gen AI has become part of logistics and supply chain organizations too, and contributes to efficiencies and automation. However, there are broader socio-economic issues with the use of these technologies regarding the transformation of the workforce, the alteration of job roles, changing skill requirements, and the adaptation of organizations. Though the literature has been widespread in considering artificial intelligence in technological and productivity approaches, there are scarce studies about how the workforce is experiencing and perceiving the socio-economic impacts of Generative AI in organizational contexts, especially in the logistics and supply chain industries. This work bridges this gap by exploring how Generative AI has social-economic effects on transforming the workforce within logistics and supply chain companies in Finland.

The purpose of the research was to understand how workers experience and predict change in work practices, organizational processes, communication, skills requirements and human-AI collaboration upon the introduction of Gen AI technologies. The theoretical framework of the study was based on Socio-Technical Systems (STS) theory and Punctuated Socio-Technical Change (PSTC). The study adopted a qualitative research design using an abductive approach. Data were gathered empirically with the help of seven semi-structured interviews with the employees and managers who were employed in the logistics and supply chain organizations in Finland, particularly in Helsinki, Tampere, and Vaasa cities. The collected data were analysed using Abductive thematic analysis with the help of NVivo software.

The findings suggested that Gen AI is progressively becoming an encouraging tool in logistics and supply chain organizations because it improves the efficiency of workflows, reduces repetitive processes, accelerates the speed of information processing, and supports in operational decisions. Gen AI was received helpful as employees perceived it as a co-working tool and not a replacement for human labour. However, the results have also revealed challenges related to workforce adaptation, the increasing skills demands, technological dependence, doubts about the safety of information, and the uncertainty of future employment structures. The results also indicated that human supervision is still necessary in Gen AI assisted workplaces where issues pertaining to reliability and contextual accuracy of the AI-generated outputs exist. The study contributes to the existing literature with the qualitative empirical understanding of how the introduction of Gen AI affected employees in logistics and supply chain organisations. The study has practical implications for organizations and policymakers who seek to support workforce adaptation and human and AI integration in technological work environments.

KEYWORDS: Generative AI, Workforce Transformation, Logistics, Digital Transformation, Socio-economic impact

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Abbreviations

AI: Artificial Intelligence

Gen AI: Generative artificial intelligence

STS: Socio-Technical Systems

PSTC: Punctuated Socio-Technical Change

1 Introduction

1.1 Background of the research

In the present era and organizational environments, Artificial Intelligence (AI) has become an influential technology that shapes modern economies and businesses. Developments in big data analytics, machine learning and computing capabilities have shifted organizations towards advanced tasks through which they can deal with big data and make their decision-making operations in a better and advanced way (Acemoglu & Restrepo, 2019; Aldoseri et al., 2024). These developments are also an attainment for digital transformation in which organizations are adopting advanced technologies to become more efficient, innovative, and competitive (Awad & Martín-Rojas, 2024). With growing use of AI technologies in business process and operations, the concern regarding technology influencing work practices and structures of employment has become a key point of debate in academic literature and organizational practices.

As the adoption of AI technologies in organizations is increasing, it led to changes in labour markets and nature of work. For example, automation technologies can substitute routine and repetitive jobs and at the same time it can generate new jobs that require high level of digital, analytical and problem-solving capabilities (Acemoglu & Restrepo, 2019). Previous studies have emphasized that the impact of technological innovations in organizations is most likely to be reorganization of work activities, modification of skills needed and generation of new professional positions (Pérez & Falótico, 2019). These developments and changes point to the fact that AI integration not only affects productivity and efficiency but it also transforms workforce composition and dynamics in different sectors.

The advancements in artificial intelligence have given rise to generative AI tools which generate new content in form of text, pictures and digital product forms (Feuerriegel et al., 2024). Through the help of generative AI systems, organizations can automate knowledge-intensive processes such as information generation, digital communications and documentation generation which are based on big data and computational models (Brynjolfsson et al., 2023; Feuerriegel et al., 2024).

In contrast to previous automation systems, generative AI can assist in decision-making, create content, and help in knowledge-making processes (Brynjolfsson & McAfee, 2014). These capabilities have expanded the usage and applications of AI technologies in modern organizations especially in environments that deal with digital collaboration and information processing.

The development of artificial intelligence technologies has also contributed to the digital transformation of data-intensive sectors of logistics and supply chain management. Organizations integrate in generative AI based systems in their workflows for assistance in their automation, data-driven decision-making and predictive analytics (Brynjolfsson et al., 2023). Moreover, the capabilities of generative AI help employees to cooperate with systems through creation and generation of insights, reports and problem solving processes through algorithms (Feuerriegel et al., 2024). According to researchers, this type of human and AI collaboration is a new kind of hybrid intelligence in which human cognitive ability is reinforced through the help of AI based systems (Jarrahi, 2018). As a result, generative AI is transforming knowledge work and information intensive work of organizations.

In the sector of logistics and supply chain management, AI and data-driven technologies are increasingly integrated in organizations. For example, organizations use predictive analytics, demand forecasting and smart planning or their logistics activities (Srivastava et al., 2022; Zhao et al., 2024). These technologies also have potential to assist in optimization of routes, inventory planning, and real-time decision-making in the complex supply chain environments in the logistics operations (Cadden et al., 2022; Lei et al., 2024). These technologies enable organizations to process large data sets operations and enhance efficiency in resource management processes and logistics planning (Kumar & Nayyar, 2020; Maddikunta et al., 2022). Therefore, the development and evolution of Generative AI has made organizations to think on improving their digital coordination and knowledge based decision decision-making in logistics and supply chains sectors (Maddikunta et al., 2022; Srivastava et al., 2022; Zhao et al., 2024).

While generative AI technologies can provide opportunities for enhancing productivity and innovation it can also pose the relevant socio-economic concerns related to their effects on employment and workforce. For example, automation technologies may reduce labour who do routine or repetitive tasks and need more workers who can handle AI-generated output (Acemoglu & Restrepo, 2019). Similarly, generative AI can automate activities such as content creation, communication and information search that were previously done by human workers (Brynjolfsson et al., 2023). This development shows that technological changes can be a source of both new job creation and changes in nature of existing jobs as well as skills needed at the same time (Acemoglu et al., 2022; Wach et al., 2023).

Along with the economic consequences, the implementation of Gen AI systems at workplace also results in significant social aspects in terms of employee well being, organizational relationships, and work quality. Employees can find both opportunities and challenges in their contact with AI technologies, such as the changing job responsibilities, high expectations of their performance, and the necessity to develop their skills constantly (Wach et al., 2023). Therefore, understanding how employees feel and react to these changes has become a significant area in studies of workforce transformation and the impact of Gen AI on workforce and Socio-economic factors raises the need to look beyond the narrow impact of adoption of generative AI in workplaces to its wider societal effects.

Generative AI technologies usage in the organizational systems has led employees to gain new competencies associated with digital literacy as well as data interpretation and interaction with intelligent systems. The employees need to know how to cooperate with AI systems and how to comprehend the results of their algorithms. They also need to comprehend how to apply these findings to the decision making activities of their organizations (Liang et al., 2025). Companies must hence consider investing in reskilling and training programs which can empower employees to fit in changing and evolving technological contexts (Wach et al., 2023). The increasing relevance of these competences reveals overall shift in work where human capabilities are increasingly replaced by AI systems and more become supplementary to them.

Although there is currently increasing literature on the topic of artificial intelligence and generative AI within scholarly literature, much of the current literature has predominantly concentrated on the technological capabilities of AI systems and their application in practice. There is comparatively less research on the role of generative AI technologies on workforce transformation through the employee lens, which involves employees who access the technology in their daily workplaces (Brynjolfsson et al., 2023). Since the adoption of the technology can be accompanied by the organizational changes that might alter the job description, skills, and work organization, the perception and experience of employees can be especially valuable (Acemoglu & Restrepo, 2019; Wach et al., 2023). Investigating these questions can thus be useful in providing a deeper insight into the overall socio-economic consequences of the adoption of generative AI in the modern organization, and how workers view the changes that come with these technologies. Their experiences and perceptions can give important information on how technological developments are reorganizing work activities, skills needed and organizational designs. These findings are crucial to those organizations, policymakers, and scholars who want to be knowledgeable about the larger socio-economic consequences of generative AI and may help in guiding the creation of efficient approaches to managing technological change in the workplace.

1.2 Research gaps

During the past several years, numerous scholars have studied artificial intelligence (AI) and digital transformation in many areas and sectors. The studies of what AI can do to streamline work and to make it better and more creative in businesses are frequent (Aldoseri et al., 2024; Awad & Martín-Rojas, 2024). Another issue that researchers explore is the application of AI in automation, decisions, and data management of companies that operate (Acemoglu & Restrepo, 2019). These works demonstrate that AI may disrupt industries and also assist organizations to perform better.

Much of the research is done on the impact of automation and AI on employment and the economy. Previous studies indicate that new technologies improve the quantity of jobs, types of jobs produced, and work division within businesses (Acemoglu & Restrepo, 2019). The other researches discuss the impact of AI and automation on eliminating routine work but also on forming new positions requiring a high level of digital and analytical skills (Acemoglu & Restrepo, 2019; Autor, 2015). These works are helpful in shedding light on the impact of technology on the economy and how it transforms the way in which individuals work.

The other major field of investigation concerns the fit of AI in digital transformation. The researchers have looked at the way companies embrace digital technologies with the aim of enhancing the way they operate, support their learning process and generate new ideas (Awad & Martín-Rojas, 2024). The recent studies also demonstrate that AI assists in strategic decisions, data-driven management, and the capacity to remain resilient with the shifting business environment (Aldoseri et al., 2024). These results highlight the fact that AI becomes more significant in determining the structure of modern companies and competition strategies.

Even though recent studies on AI and digital transformation reveal an increasing number of exploration the majority of the works embrace the technical aspect, the utilization of tools, and the economic results. Numerous studies point to the acceleration of the work process by AI, its automation, and increased innovation within companies. There is scarce enquiry on the impact of the implementation of Gen AI tools on the employees who interact with it regularly (Bhargava et al., 2021). It is particularly significant to know the vision of employees, as technological alterations tend to alter the way things are performed, job roles, and the required competencies.

Moreover, generative artificial intelligence is a relatively new concept in artificial intelligence work. Generative AI technology has the potential to generate a new work and offer knowledge-intensive functionality to tasks like communication, analysis, and information creation (Feuerriegel et al., 2024). Although the tools have become increasingly popular in academia and the workplace, comparatively little study has been conducted concerning the influence on transformation of workforce by these tools. We are yet to better understand the ways in which generative AI is transforming the way work is done, the skills required, and ways organizations operate in particular industries.

A particularly topical area of the study of these developments is the logistics sector. It is becoming more common that logistics processes use data-intensive technology and digital systems to operate complex processes such as planning, routing and real-time decision making (Burnham, 2024). Although previous research has indicated the practical advantages of AI in logistics and supply-chain management, there is a limited number of investigations that examine the effects of this Gen AI on the aspects of labour and workforce shift and employee experience in logistics companies.

In addition, technology change research examined through a technical and economic lens pays insufficient attention to the merging of people and technology when introducing new technologies to a firm. In a sociotechnical perspective, new technology will relate to people, the company structure as well as the way work is handled, and this comes with major adjustments in the way the workplace is operated. These interactions are valuable to understand when disruptions in technology influences the habits, skills and what workers believe according to their perception. Thus, there is a need to study the social and economic impacts of using generative AI in companies, particularly through the lens of employees who will directly face the change. This dissertation examines the impact of generative AI on the workforce in the logistics industry in Finland. By studying what employees think and experience when adopting Gen AI, the study will provide a better understanding of how technology changes the work tasks, organization´s practices and required skills.

1.3 Research problem, objectives, and research questions

The adoption of Generative AI in organizations is seen to be increased rapidly especially due to its ability to support decision making process, communication and knowledge creation

(Brynjolfsson et al., 2023; Feuerriegel et al., 2024). Previous literature indicates that Generative AI technologies have emphasized on increasing productivity, efficiency, operational performance, technological capabilities and macro-level outcomes (Acemoglu & Restrepo, 2019; Brynjolfsson et al., 2023). However, the introduction of generative AI is also associated with socio- economic changes including changes in job tasks, skill demands, and the workforce structures (Acemoglu et al., 2022; Burnham, 2024). Despite of developments of Gen AI, there is still limited understanding of how generative AI transforms the work practices and experiences of employees in organizational contexts in the current literature. There is currently a scarce understanding of the role of generative AI in workforce transformation from an employee point of view working in logistics sector. Consequently, more research is needed to examine the impact of generative AI on workforce transformation at an employee level.

Based on this, the present study aims to study socio-economic impact of generative AI on workforce transformation in logistics sector in Finland. The study is aimed at comprehending how employees view and experience changes within an organization and work with regard to the implementation of generative AI technologies. Therefore, the objectives of the study are:

- To examine the socio-economic impacts of generative AI on workforce transformation in Finland's logistics sector.
- To explore how employees perceive and experience Gen AI in logistics sector.

Based on these objectives following questions are proposed:

- How do workforce of logistics sector perceive socio-economic changes after adoption/introduction of Generative AI?
- What are the perception and experience of workforce on changes after implementation of Gen AI?

The research questions are aimed at understanding and explaining workforce changes in the context of alterations in work tasks, skill demands, organizational systems, and work experiences of the employees after the adoption of generative AI.

1.4 Research design and contribution

This paper seeks to create a greater insight into the influence of generative AI adoption on the transformation of the workforce in the logistical industry. Specifically, the research aims at investigating the perception and experience of employees on socio-economic shifts in the workplace in the context of the introduction of generative AI technologies within the organizational setting. The research design to be used in the study is a qualitative exploratory research design to achieve this. Qualitative research methods work well to study areas of complex organizational phenomena and to comprehend the way individuals interpret and experience technological and organizational changes within their work settings. The study intends to record the in-depth information about the perceptions, interpretations, and experiences of the employees of the implementation of the generative AI technologies within the logistics sectors through the qualitative inquiry.

The study's theoretical framework is based on the Punctuated Socio-Technical Change (PSTC) and Socio-Technical Systems (STS) theory. The socio-technical systems theory focuses on the interrelation of the technological systems and the social structures in organizations and how the change in technology impacts the work processes, organizational structures, and roles of human beings. PSTC enhances to this view through the way technological advancements can establish areas of swift change in socio-technical systems with the resultant change of both the organization and the workforce. In the context of this paper, generative AI is discussed as a technological innovation, that interrelates with structure of organizations, work processes, and job roles. The research thus examines how adoption of Gen AI technologies have influenced workforce transformation especially regarding skill requirements, work tasks and organizational practices.

The empirical investigation of this study will be conducted through semi-structured interviews with employees and managers employed in logistics organizations. The interviews will enable the participants to narrate their experiences, perceptions and thoughts about the use of generative AI technologies in the workplace. Semi-structured interviews are especially suitable in addressing emerging technological phenomena since they offer flexibility in the study as they seek to address the views of the participants and ensure consistency in the interviews. Data obtained via interviews will be processed through thematic analysis, where a specific approach will enable the determination of the common themes and patterns regarding the experiences of the employees with the adoption of the generative AI and the workforce change.

The results of the study will provide input into the theoretical and practical discourse on the socio-economic impacts of generative AI. Theoretically, the presented study will provide its contribution to the literature on socio-technical change and analyze the notion of workforce transformation in the terms of the integrated approaches of STS and PSTC. Practically, the study will offer implications to organizations operating in the logistics industry as it emphasizes the perceptions and experiences of the employees of introducing the generative AI technologies and the impact of the technologies on the working practices and skills needed. This research aims to understand how the new AI-based technologies transform the workplace setting and the workforce structure in modern enterprises by examining the perceptions and experiences of the adoption of generative AI.

1.5 Structure of the study

This dissertation is divided into six chapters. In chapter 1, the background is presented to introduce the topic of the research, the research gap, the research problem, objectives, and research questions. The research design and theoretical perspectives to follow the study are also explained in this chapter. Chapter 2 contributes to theoretical background of the research. It analyzes the literature available regarding artificial intelligence, generative AI, and workforce transformation. The chapter also presents the theoretical background of the research, among which are Socio-Technical Systems (STS) and Punctuated Socio-Technical Change (PSTC) that offer the conceptual framework to study the transformation of the workforce in response to technological change. Chapter 3 will explain the research approach that will be used in the study. It will describe the qualitative research design, the methods of data collection, and the data analysis methods of the study. The chapter will also mention the application of semi-structured interviews and thematic analysis as the major methods of analyzing the perceptions and experiences of employees concerning the adoption of generative AI. Chapter 4 of the dissertation will explain the results of the study. The analysis of the interview findings will be provided and structured into themes according to how the employees perceive generative AI implementation and the effects on their perceptions, work activities, their skills, and work practices. Chapter 5 will explain the findings based on the theoretical framework and the past literature. This chapter will build the interpretation of the empirical findings and discuss how the findings can contribute to the existing literature on generative AI, socio-technical change, and transformation of the workforce. Finally, Chapter 6 will discuss the conclusion of the dissertation that will summarize the overall findings of the study, interpret theoretical and practical implications, and will provide limitations and the future research directions.

2 Literature Review

2.1 Generative Artificial Intelligence

In the artificial intelligence field Gen AI has emerged as a famous trend, which is the process of generating new content such as text, images and data by learning pattern on large volumes of data (Dwivedi et al., 2023). Compared to the conventional artificial intelligence systems that are mainly used to predict, classify, and optimize, Gen AI can be used to create content and generate knowledge, increasing the functional range of artificial intelligence in organizations (Gozalo-Brizuela & Garrido-Merchán, 2023; Yu & Guo, 2023). It has been made possible through the advancement of techniques of machine learning, especially deep learning systems that can process unstructured information such as unnatural language and multimedia input (Goodfellow et al., 2018; Spektor et al., 2023). Due to this fact, every output generated by Gen AI systems can be quite similar to that made by humans, which is why they become more applicable in the knowledge-intensive environment (Knott et al., 2023; Ooi et al., 2025). The rapid spread of these technologies demonstrates their ability to reshape business operations and improve organizational capabilities (Harreis et al., 2023; Sirtori & Case, 2023). Thus, generative AI is becoming a groundbreaking technology, which not only automates tasks but also aids in creativity and innovation in modern organizations (Dwivedi et al., 2023; Grewal et al., 2025).

The importance of Gen AI is interrelated with the concept of digital transformation when organizations are integrating new technologies to improve their performance, flexibility, and decision-making capabilities (Davenport & Mittal, 2023; Ooi et al., 2025). In this regard, generative AI becomes the focal point where organizations can generate insights, automate their communication, and facilitate decision-making in dynamic environments (Brynjolfsson et al., 2023; Financial Times, 2023). Its capacity to integrate and process large amounts of structured and unstructured data enables companies to further improve performance across operations and react better to the evolving market environments (Gaessler & Piezunka, 2023; Sirtori & Case, 2023). Moreover, the automated AI systems are becoming part of organizational processes, and they help automate many processes, including reporting, future projections, and content creation, therefore being more productive and consuming less effort (Dwivedi et al., 2023; Harreis et al., 2023). This convergence signifies a move towards a more intelligent and flexible automation which will be capable of performing both daily and complex tasks (Budhwar et al., 2023). Consequently, generative AI turns out to be one of the facilitators of digital transformation plans in various industries, including logistics and supply chain management (Sharma, 2023).

One of the foundational differences between generative AI and other AI systems is that it can produce new information while also processing information rather than only analysing data (Goodfellow et al., 2018; Kaplan, 2019). The use of traditional AI systems has been predominantly applied in solving problems in structured environments, including forecasting, classification, and optimization, whereas the generative AI allows more flexible and adaptive applications by taking advantage of newer learning methods, including unsupervised and reinforcement learning (Martínez et al., 2023). Such an ability enables the use of generative AI in various knowledge-intensive tasks and processes, such as natural language processing, content creation, and decision support, which gain greater significance in contemporary organizations (Gozalo-Brizuela & Garrido-Merchán, 2023; Knott et al., 2023). As a result, generative AI has a privileged place in the artificial intelligence systems, in that it occupies the intermediary space between analytical and creative capabilities and allows systems to fulfill the tasks that can involve both a reasoning process and content creation (Ooi et al., 2025). This feature makes it more relevant where organizations need to handle large volumes of data and generate actionable insights in real time (Gaessler & Piezunka, 2023). Consequently, generative AI is starting to be viewed as a major source of innovation and competitiveness in modern organizations (Grewal et al., 2025; Harreis et al., 2023).

Apart from technical functions, GenAI has significant consequences on the ways of organizing and executing work in organizations, especially in knowledge-intensive setting (Jarrahi, 2018). GenAI is involved in transformation of job roles and the redistribution of tasks between humans and machines such as allowing systems to obtain work abilities like writing, communication, and problem-solving (Valentine, 2026). This is a transformation that employers must prepare the workers to acquire new skills and adjust to workflows that will change, especially regarding digital literacy and the possibility of understanding the results provided by AI (Sharma, 2023; Wamba et al., 2023). Human and AI collaboration is also made possible by GenAI in order to enhance human capabilities with the help of information based data and automation of repetitive work (Davenport & Mittal, 2023). It helps productivity of organizations and also maintains human supervision in decision making (Brynjolfsson et al., 2023). Therefore, GenAI is more than a technological phenomenon and an example of a socio-technical phenomenon that changes organizational systems and the nature of work (Feuerriegel et al., 2024; Valentine, 2026).

The literature shows that there are several ethical, corporate and societal issues linked with GenAI as well (Budhwar et al., 2023). For example, transparency, accountability, biasness, and data confidentiality issues, especially in areas where governance and decision-making are involved (Gozalo-Brizuela & Garrido-Merchán, 2023). The adaptation of GenAI also increases issues of reliability and trust especially in complex organizations (Financial Times, 2023). In such cases it is essential to create appropriate regulatory frameworks and organizational policies to address such risks (Davenport & Mittal, 2023; Grewal et al., 2025). Companies also should consider technological potential as well as its impact on society, employment shifts, skill levels, and labor relations (Brynjolfsson et al., 2023). Therefore, to have the complete picture of generative AI, it is necessary to pay attention to its technological capacity and address its overall implications on organizations and society (Feuerriegel et al., 2024).

2.2 Gen AI in Logistics and Supply Chain Contexts

The generative AI is becoming increasingly popular in the logistics and supply chain companies as it assists the transformation of work processes, coordination, and decision-making process in complex operational conditions (Wamba et al., 2023). Logistics companies work in data-intensive environment, which needs constant coordination of numerous actors, and generative AI allows on-demand processing of large amount of structured and unstructured data to support the work (Ooi et al., 2025). This aspect assists logistic organizations to develop insights, promote awareness of situation, and improve its responsiveness to the changing situations of operations (Sharma, 2023; Sirtori & Case, 2023). In the meantime, generative AI can be employed to create content and use pieces of knowledge based on analysis in addition to the traditional analytical systems and help in decision-making and communication within the organization (Dwivedi et al., 2023). These organizations are therefore beginning to use generative AI in their logistic and supply chain operations to make them more efficient and flexible (Gaessler & Piezunka, 2023).

Generative AI has wide applications in knowledge-intensive tasks, such as reporting, communication, and information processing, in the logistics sector, which are significant in daily operations and activities of the supply chain networks (Wamba et al., 2023). Gen AI systems can also create reports and summarize operational data as well as facilitate communication of stakeholders, which can decrease the number of individuals who need to work manually in logistics companies and enhance their accessibility (Awan et al., 2021; Financial Times, 2023). These applications emphasize how generative AI contributes to adding value to human resource since employees will be communicating with AI systems to conduct their tasks more effectively instead of substituting human labor with the automation (Jarrahi, 2018). Moreover, generative AI encourages routine processes automation and streamlining, as well as allows employees to focus on higher value and decisions based work (Budhwar et al., 2023; Grewal et al., 2025). This is especially applicable in the field of logistics, where AI outputs are used to aid quicker and more efficient decision-making during planning and coordination tasks (Sharma, 2023). As a result, generative AI can help to transform the nature of knowledge work in the logistics organizations by combining human knowledge and machine-based knowledge (Feuerriegel et al., 2024).

The use of generative AI is also significant in the field of decision-making in logistics and a supply chain setting, where it assists in gathering data-based insights and scenario analysis (Wamba et al., 2023). Under the condition of uncertainty, AI systems can come up with recommendations and simulate various outcomes of operations when data is provided, which gives the managers the chance to consider the alternatives and make better choices (Goodfellow et al., 2018; Kaplan, 2019). This enhances the level of quality of decisions, as it allows conducting more systematic and evidence based management of logistics activities (Yu & Guo, 2023). Nevertheless, this growing dependence on AI brings about the problem of trust, transparency, and accountability, especially, when the process of making a decision is affected by complex algorithms (Budhwar et al., 2023). These issues reinforce the idea that logistics organizations need to create governance frameworks and make sure that the human factor is an intrinsic component of the decision making process (Dwivedi et al., 2023). With increased integration with supply chains, generative AI is one contributor to a more general change in focus by adopting data driven and technology based decision-making practices (Grewal et al., 2025; Harreis et al., 2023).

Moreover, the logistics organizations implementation of generative AI has extensive implications on how organizations coordinate and collaborate within the supply chain networks, where different stakeholders support one another by communicating and exchanging information in real time (Sharma, 2023; Wamba et al., 2023). Generative AI helps to structure communication more effectively and minimize time waste during information transmission among partners in the supply chain by introducing the ability to generate reports automatically in real time, and access shared information (Sirtori & Case, 2023). This feature improves how the logistics companies can deal with complicated operations and react suitably to the supply chain interruptions (Sharma, 2023). Moreover, AI can foster teamwork by giving employees valuable information and advice and enhancing their adaptability to a data driven and dynamic workplace setting (Feuerriegel et al., 2024). Consequently, the logistics and supply chain organizations have been increasingly using generative AI to enhance integration, coordination, and overall operational performance (Davenport & Mittal, 2023). Such a change is representative of a wider trend towards digitally empowered logistics organizations in which technology becomes the key driver of work processes, communication and collaboration (Jarrahi, 2018; Valentine, 2026).

2.3 Task and Work Transformation

In logistics and supply chain sector, generative AI usage is becoming noticeable because it helps in transformation of work processes (Wamba et al., 2023). In that regard, information processing, coordination, and reporting tasks are becoming much more backed by digital technologies, allowing more effective processing of large amounts of data (Ooi et al., 2025). This is a transition to the old methods of handling tasks to workflows, whereby employees are able to engage technological systems as part of their daily tasks (Valentine, 2026). Due to this, work becomes more oriented towards managing and interpreting information and does not involve strictly manual or repetitive work (Lagorio, 2022). Additionally, digital systems can work towards enhancing uniformity and acceleration in the provision of service, especially within an environment that is rich with complex and dynamic activities (Sharma, 2023). The result is a slow reorganization of work, as employees become more involved in control and organization of processes with the help of technology (Awan et al., 2021). Accordingly, generative AI helps to redesign the organization and performance of tasks in the logistics process (Wamba et al., 2023).

One of the central factors behind this change is the reallocation of work between humans and the technological systems, specifically the growing use of automation in the daily process (Kmiecik & Skórnóg, 2025). Digital systems assist and automate tasks like documentation, data entry, or analysis, and reduce the need of continuous human involvement to perform these activities (Ooi et al., 2025). Meanwhile, tasks that necessitate contextual cognition and decision-making, especially where it comes to uncertainty or complexity, continue to fall on the shoulders of employees (Jarrahi, 2018). It describes a symbiotic connection between humans and technology when the systems help in doing the work, yet human participants of the process are still in control and are accountable (Brynjolfsson, 2025). Employees will therefore have to define results generated by AI products and apply them to some scenarios within operations (Feuerriegel et al., 2024). Such a cognitive and evaluative shift adds significance to the task performance activities (Dwivedi et al., 2023). Consequently, generative AI helps in reorganizing the human and technological roles in the logistics processes (Kmiecik & Skórnóg, 2025).

Other broader work processes that are affected by generative AI include the option of having more integrated and responsive workflows in logistics and supply chain operations (Sharma, 2023). The systems based on AI can provide more rapid access to data, as they enable employees to react to the needs of the functioning process and altered circumstances more effectively (Wamba et al., 2023). This boosts the integration of various functions and facilitates greater flow of information in logistics networks (Ooi et al., 2023). Moreover, digital technologies can also lead to increased consistency in outputs, which facilitate the standardization of some processes of operation (Awan et al., 2021). Nevertheless, the introduction of these systems also involve employees changing their work habits, such as communicating with AI tools and using generated outputs in their work (Valentine, 2026). This adds other duties associated with the tracking and assuring the system outputs (Lagorio, 2022). That is why generative AI is not only influential in the work of individual agencies but also in the structure of the working process and its coordination in a logistics organization (Sharma, 2023).

The interaction between humans and AI is an essential part of transformation of tasks, and workers have begun to cooperate using technological tools, rather than working in isolation (Jarrahi, 2018). In logistics and supply chain sectors technological advancement of generative AI can help workers and support them with various information and solutions required for task completion (Shatat & Shatat, 2025). This creates a collaborative working environment in which human judgment and technological products are combined with each other (Brynjolfsson et al., 2023). Therefore, it is mandatory that employees refine and interpret the outputs of a system as a part of their work (Feuerriegel et al., 2024). It results in increased iterative workflows, in which the tasks are constantly edited in accordance with new information (Dwivedi et al., 2023). Simultaneously, the necessity of the supervision cannot be ignored, and employees must see that the results are reliable (Lagorio et al., 2022). Human and AI cooperation thus emerges as a characteristic trait of performing tasks within the logistics organisations (Jarrahi, 2018).

Lastly, the transformation of work using generative AI is among factors that foster progressive job redesign in logistics and supply chain business entities (Mohamed, 2024). Employees concentrate more on analytical, coordinative, and decision-based activities as more tasks they perform at their workplace are being aided by digital systems (Wamba et al., 2023). It is more of a shift to execution-based positions and roles that entail the supervision and interpreting of the system output (Kmiecik & Skórnóg, 2025). The employees are supposed to use digital tools and process information, as well as make sure that the choices are made in line with the needs of the company (Awan et al., 2021). This transition also demands constant readjustment of work as it becomes more reliant on technological systems (Sharma, 2023). Role limits are also more adaptive due to the distribution of roles, as human beings and systems share the tasks (Lagorio, 2022). So, generative AI belongs to the function of changing the profession status and structure of tasks of workers in the logistics environment (Valentine, 2026).

2.4 Skills and Reskilling

The introduction of artificial intelligence (AI) into the organizational setting is closely linked with the changes in organizational structure, processes, and the practice of decision-making. AI helps organizations to work with extensive datasets and create predictive information, thus facilitating more confident and active decision-making under challenging and more dynamic conditions (Belhadi et al., 2021). Meanwhile, AI based systems can automate daily operational processes like forecasting, inventory management, and planning that decrease the number of manual activities and improve efficiencies in every organizational process (Balasubramanian et al., 2023). This change indicates a transformation from traditional process-oriented structures to data and digitally enabled organization that focuses on responsiveness and adaptability (Dubey et al., 2022). AI also helps increase organizational coordination through real-time exchange and combination of a variety of data sources and increase the operational performance of the whole organization (Jiao et al., 2022). This has led to the incorporation of interdependent and technology enabled systems in organizations, which facilitate ongoing optimization and integration of activities (Chen, 2019). As a result, AI based change necessitates companies to restructure their processes and structure so that they can leverage on digital technologies efficiently to stay competitive in the rapidly changing environments (Wu et al., 2023).

The organizational change enabled by AI can also be seen in the transformation of the decision-making processes, as the traditional intuition-based approaches are being replaced out by data-intensive and analytical strategies. In order to enhance quality of decision making and to reduce uncertainty AI predictive analysis help organizations to forecast demand trends, disruptions and enhance resource allocation (Jauhar et al., 2024). Because of these predictions organizations become more responsive to new market environments (Carvalho et al., 2022; Ivanov & Dolgui, 2021). Apart from this, artificial intelligence also helps to minimize human error and creates consistency in decision-making process (Rodgers et al., 2023), but human experience in decision-making should also be considered important along with trust in AI systems (Rastogi & Pandita, 2025). This creates a hybrid decision-making framework in which human and AI systems collaborate in better decision-making (Tschang & Almirall, 2021).

The use of AI has a significant impact on organizational learning, growth, structure and decision-making. AI supports those organizations which are involved in dynamic environment by allowing the analysis and processing of huge and complex information (Akter et al., 2022). This idea of dynamic capability emphasizes the relevance of the knowledge of the organization in terms of redesigning resources and adjusting to new circumstances, which is important in the context of AI (Teece et al., 1997). Organizations operating in high velocity environments have to acquire capabilities of learning more than one dimensionality and integration with exploration and exploitation in continuous learning cycles (March, 1991). This change is a challenge to the traditional model of organizational learning and demands more flexible and versatile to knowledge management (Eisenhardt & Martin, 2000). Moreover, the AI based change expedites the innovation process and allows organizations to deliver new insights and come up with new solutions, which makes them more competitive in the long term (Awan et al., 2021). As a result, AI not only enhance the ability to achieve operational efficiency, but also increases the organizational flexibility and innovation.

The other crucial aspect of organizational change is the change in organizational structures and functions of the workforce as AI reallocates workload between individuals and smart machines.

Automation based on AI also does not mean having to perform manual tasks more frequently, but it makes more analytical, creative, and decision-oriented tasks more significant (Acemoglu et al., 2022). This change will compel the workforce to acquire new skills associated with digital technologies, data analysis, and problem-solving so that they could be effective in an AI-driven setting (Brynjolfsson et al., 2023). Meanwhile, AI also brings in new ways of human and machine work, where employees engage in communication with intelligent systems to carry out their duties more efficiently and effectively (Konuk et al., 2023). This hybrid model changes the nature of work, where human experience combines with machine understanding (Makarius et al., 2020). The organizations have to create appropriate policies and strategies to tackle the issues comes along with AI introduction such as regarding employment displacement, job ambiguity, and workforce adjustment (Sison et al., 2023). Hence, AI driven organizational restructuring not only transforms the operating processes but also reconstructs the workforce relationship and even the essence of work.

Lastly, the introduction of AI into organizations has more extensive implications to the organizational culture, governance, and strategic development in the long term. The implementation of AI requires organizations to establish a culture of an ongoing learning process, flexibility and innovation to ensure they adequately adjust to the changes in technologies (Bhargava et al., 2021). Leadership will become a key component of controlling the transformation associated with AI usage that will be instrumental in making sure that such technological endeavors are anchored in the organizational objectives and that the workforce will be assisted in the process of making the necessary changes (Senadjki et al., 2023). Meanwhile, organizations should tackle the ethical and regulatory issues that accompany the implementation of AI, such as the challenges of transparency, accountability, and data governance (Khogali & Mekid, 2023). AI based changes promote implementing more flexible and adaptable organizational frameworks that preserve continuous enhancement and creation (Hoessler & Carbon, 2024). This leads to the conclusion that organizational change within the framework of AI is more intricate and multifaceted, as they involve not only technological change but cultural, managerial, and institutional change as well, thus reflecting the multidimensional nature of AI based organizational change today.

2.5 Socio-Economic Impacts

Due to the rapid development of generative artificial intelligence, there has been significant socio-economic changes altering the way knowledge is generated, distributed, and used among industries. GenAI systems allow producing new contents and knowledge through large-scale data, improving pace of innovation and contributing to the invention of new approaches to generating value within companies (Dwivedi et al., 2023). This feature automates and improves knowledge based operations, decision-making processes, and enables organizations to work more effectively in complex environments (Davenport & Mittal, 2023). On a larger scale, the development of AI technologies is changing economic systems, as it is shifting the competitive landscape and creating new possibilities of data-driven business models that are based on constant information processing (Brynjolfsson & McAfee, 2014).

Among the most important socio-economic consequences of the application of GenAI is associated with its effect on labor markets, specifically, the transformation and elimination of jobs. The automation of routine and non-routine thinking tasks has sparked worries over workforce displacement as AI systems can now execute certain tasks that were formerly performed by people (Frey & Osborne, 2017). Nevertheless, it is also noted in the literature that the technological progress is more likely to generate new employment opportunities due to the mass production of more demanding and higher level cognitive, analytical, and creative skills (Autor, 2015). The move is indicative of a change in the nature of work, which is more knowledge intensive and therefore, the workforce must adapt and develop new competencies based on changes in the technological landscape (Bessen, 2019). Additionally, the adoption of Gen AI can shape labor wage distribution as it raises the returns to skilled labor and lowers the opportunity to the less skilled labor, thus contributing to possible inequalities in labor markets (Acemoglu & Restrepo, 2019).

Besides labor market impacts, GenAI has several significant implications on organizational productivity and economic performance. A study indicates that Gen AI boosts operational performance and it also facilitates precise and timely decision making in organizations through creating content and fast data processing. Having the capability to create predictive awareness and run alternative simulations enables organizations to feel the disruptive events beforehand and react better to uncertainty, which enhances resilience and adaptability (Ivanov & Dolgui, 2021). Furthermore, GenAI makes it easier to spread knowledge in large scale so that organizations can gain easier access and use of information and contribute to collaborative innovation (Nonaka & Takeuchi, 1995). This helps in creating knowledge-based economies where value creation is being rooted more in the creation and use of information.

Another socio-economic aspect of GenAI is changing the structure of work and its human and AI relationships. By implementing AI within the processes of organizations, hybridization systems arise whereby human knowledge and the machine products are synthesized to improve performance and the quality of decisions (Jarrahi, 2018). By redefining roles on the concept of human and GenAI technologies, these systems transform traditional work arrangements and the way people perform it (Brynjolfsson et al., 2023). Meanwhile, the fact that AI depends on it more creates issues as to trust, transparency, and accountability, especially with decision making processes that are manipulated by complicated algorithms (Raisch & Krakowski, 2021). Consequently, organizations have had to come up with new governance structures so as to control the human and AI interaction, and so as to promote successful interaction between human and technological entities.

Along with its positive aspects, GenAI use also leads to important ethical and societal challenges that should be managed to be implemented responsibly. This is especially problematic in terms of bias and fairness because AI systems can either recreate or enhance inequalities that training data has (Mehrabi et al., 2021). GenAI use significant amount of sensitive and personal data which leads to data privacy and security issues (Zuboff, 2019). In dynamic environments accountability and explainability of AI decision-making is very concerning because incorrect or biased results can have significant impact (Taddeo et al., 2019). Consequently, the socio-economic effect of GenAI is dual by its nature because it is both an opportunity to innovate and be efficient at the same time but also poses threats that must be adequately controlled and regulated.

Socio-economic consequences of generative AI are critical in the context of logistics and supply chain, where heavy sets of data and coordination in work are required. According to Wamba et al. (2023) GenAI helps in planning, forecasting, and coordination and decreases manual decision making and redefines operational roles. In the context of logistics, this change turns the workforce towards doing less work and more analysis, as well as supervising roles, since employees have to handle the insights produced by GenAI and to control digitally empowered systems (Ivanov & Dolgui, 2021). Simultaneously, the introduction of GenAI in warehousing and transportation processes guides changes in the nature of jobs, with routine (physical and administrative) duties declining and those associated with monitoring and decision support growing (Kache & Seuring, 2017). This shift is also one of the factors that polarize the workforce, with more people who demand high skills and those who can work with high skilled employees becoming more in demand, and lower-skilled jobs losing their positions to GenAI (Lorentz et al., 2021). Moreover, the AI-powered logistics systems boost real-time coordination and visibility throughout the supply networks that boosts effectiveness but adds stress to work, creating demands on responsiveness and constant performance (Wamba et al., 2024). As a result, not only does the implementation of GenAI in the logistics domain enhance efficient operations but it also changes how labor is organized, skills required, and the work itself in the supply chains business.

On the whole, socio-economic consequences of GenAI demonstrate the complex interaction between technical progress, the transformation of the labor force, and organizational changes. Although the productivity level is increased, innovation is promoted, and new types of value creation are possible, GenAI transforms labor markets, changes the skills needed, and poses significant economic and social challenges. It follows that by knowing these effects, organizations and policymakers interested in utilizing GenAI effectively can do so and maintain inclusive and sustainable growth in an increasingly AI driven economy.

2.6 Employee Experience and Perception

The generative artificial intelligence is fundamentally transforming the employee experience by impacting job satisfaction, work systems, motivation, and work perception in organizations. According to the literature, AI can positively affect job satisfaction in case it decreases repetitive work, and allowing employees to devote more time to more valuable, creative, and analytical activities instead of wasting time on repetitive work (Szeszák et al., 2025). This positive change in their job role is linked to better engagement and motivation, especially when employees feel safe that the use of AI enhances their potential not substituting their skills (Bankins et al., 2024). Simultaneously, AI systems can also lead to a decrease in job satisfaction as they cause uncertainty over job security or the change of the existing roles limitation without adequate organizational support (Alcover et al., 2021). Moreover, the absence of transparency produced by AI may diminish trust and cause frustration, especially when workers cannot comprehend and question the choices made by the systems (Khogali & Mekid, 2023). In that regard, the role of technology efficiency in making employees satisfied is not exclusive in the implementation and integration of AI into routine workflows.

The introduction of AI brings considerable stress and workload change, which can be considered a shift in physical work to cognitive and monitoring intensive jobs. Although automation will decrease the physical labor supply and enhance operational performance, it will also place more cognitive load on employees since they will be expected to interpret and verify AI-generated output (Szeszák et al., 2025). This shift is associated with the work intensification as Gen AI operated environment places more demands on speed, accuracy, and responsiveness at any time (Bankins et al., 2024). These systems have algorithmic management and monitor performance that may give the impression of reduced autonomy and increased surveillance which leads to increased workplace stress (Khogali & Mekid, 2023). These issues are also accelerated by the rapid change of the technology and the lack of proper training since employees have to keep up with the changing systems and acquire new skills to be effective (Alcover et al., 2021). Consequently, despite its efficiency, AI results in the emergence of new types of psychological pressure that companies have to address proactively.

The level to which AI technologies promote or limit the autonomy and growth of the employees would also greatly effect employee motivation and engagement. As employees know about Gen AI systems and can scrutinize their performance, they feel they have a sense of control over their job, thus boosting motivation and interest (Omri et al., 2025). The further possible effect of AI on motivation is also the enhancement of the task performance and ability of the employees to obtain better results with the help of data-driven insights and decision support (Szeszák et al., 2025). Furthermore, intrinsic motivation and professional identity might be reinforced by an opportunity to perform more meaningful and complex tasks that is of special interest in knowledge-sensitive settings (Bankins et al., 2024). Nevertheless, motivation can decrease when staff believes that AI is taking away the aspects that define their knowledge, or restricting their input to the decision-making process (Alcover et al., 2021). The correspondence of AI usage and occupational identity is hence significant in influencing engagement and long-term motivation in organizations.

Besides being an effective motivational impact, generative AI is one of the main determinants of the perception of employees because it affects the sense of fairness, transparency, and trust in organizational activities. It is observed in literature that employees use GenAI when they believe it to be unbiased, transparent, and linked to values of organizations (Khogali & Mekid, 2023). But if GenAI is used to make decisions such as promotion or job seeking, it can reduce their engagement and they can resist (Alcover et al., 2021). Based on empirical research of HR concentrated work, GenAI enables personalization and can positively impact employee experience which is accomplished by enhancing employee learning, performance control, and developmental plans resulting in a high retention and satisfaction levels (Budhwar et al., 2023;

Feuerriegel et al., 2024). At the same time, workforce-specific concerns, such as unemployment, reduced human involvement, and lack of transparency, seem to prevail in the mindsets of workers regarding the use of AI, as detected in the survey (Nica et al., 2024). The perceptions of employees regarding AI are also influenced by the organizational practices like training, communication, and ethical governance, as those practices define how AI is experienced in the working everyday scenarios (Budhwar et al., 2023; Rane, 2023).

The above discussion shows that employees perceive GenAI to be a balance between socio-technical challenges and productivity, as GenAI can influence motivation, engagement, and job satisfaction. The reason is that it allows individuals to focus on more meaningful work and apply their capabilities over there. Apart from this, it can also create job insecurity, stress, and cognitive workload issues (Dwivedi et al., 2023). So, perception of employees depend not only on technical functionality but also on conditions and environment in which GenAI is used. Adoption strategies should thus focus on development of workforce, fairness, and transparency (Zhang & Chen, 2024).

2.7 Challenges and Risks of Gen AI

Generative AI is not always a solution since it is usually hindered by change resistance that may not only be caused by technical barriers but also by organizational inertia, anxiety among the employees and lack of knowledge of the changing job positions. The AI-provided discourse on workplace transformation was the one that compared the digital change with resulting radical changes in employee experience and work design (Tissot et al., 2020). However, more recent materials reveal that with the progress of the trend of generative AI adoption in organizations, the interest and concern about it has increased, particularly as it is being used in managing important organizational procedures, such as the recruitment, onboarding, training, and evaluation processes (Dwivedi et al., 2023). Even though Gen AI has the ability to optimize human resource operations and minimize administrative burdens, it is not embraced easily in the work environment where employees and managers lack a clear understanding of the impacts of the technology on work practices and authority to make decisions (Aguinis et al., 2024). This fear has been proven to be a fact that organizations are still facing serious implementation challenges that are linked to data security, ethics and employment behaviors (Rane, 2023). Simultaneously, cultural normativity and the inefficiency of the traditional organization to adapt to the digital change rapidly can hinder the implementation of generative AI, making resistance a structural problem and affecting individuals individually (Budhwar et al., 2023). The situation is more tangible in a situation when companies do not possess the competence to implement AI tools properly, which results in their usage being delayed and undermines the possible benefits of innovation (Podhorska et al., 2019). Although in some situations, the active integration of organizations has taken place, the success of this process depends on whether the AI is included in the existing structure in such a way that it reinforces but not suppresses the work of the organization, and it is suggested that the issue of AI adoption is more a managerial than a technological one (Zhang & Chen, 2024).

The second and the greatest challenge is trust and transparency. GenAI systems may be difficult to interpret when they influence key organizational decisions made by users when outputs are involved. The recent study on Gen AI assumes that transparency in AI can be achieved via openness, not the opposite (that is, the systems should be able to provide understandable explanations of the recommendations and actions) (Kim et al., 2020). This is particularly relevant to the field of regulation and organization in which the recent regulatory and organizational discourses are slowly turning to a focus on transparency as a prerequisite of trust, instead of an option in design (Akinrinola et al., 2024). In its conceptual expression, transparency has been associated with explainability and openness, which are necessarily at the core when organizations use AI in a decision-making situation that involves people and work processes (Larsson & Heintz, 2020). Biased information is even more critical in adapting AI to learning because discriminatory prediction might be present even in cases where users themselves are not conscious of the manner in which they came about developing discriminatory predictions (Varona & Suárez, 2022). Studies of AI bias also reveal that bias may be induced in all phases of modeling, training, and application, implying that trust can be compromised on several levels of AI implementation instead of on a failure point (Ferrer et al., 2021). When it comes to generative AI systems specifically, stereotypes and biased outputs are capable of further enhancing the existing social inequalities. Therefore, transparency cannot be separated from fairness and accountability (Ferrara, 2024). Other concerns also translate into the topic of cybersecurity, where the same generative tools used in defense, automation, and analysis can also be misused, causing users to have less trust in the overall organizational use of the technology (Gupta et al., 2023).

GenAI is more than just a matter of bias but also includes ethical concerns of privacy, surveillance, accountability, and socio-economic concerns, which are both work and organizational change issues. Due to the development of AI systems, there is a greater amount of gathered and utilized personal and behavioral data, which presents an even greater threat of privacy intrusion even in increasingly digitalized working conditions (Carmody et al., 2021). Two of these problems are that AI tools can frequently store or manipulate sensitive data in a way less visible to a consumer, and so it is easy to lose trust in organizational AI systems unless it is highly governed (Allhutter et al., 2020). The ethical issues also appear at the information ecosystem level, in which the increased usage of the AI-generated content can undermine the accessibility and quality of the human-generated public knowledge to train the next generation systems (Rio-Chanona et al., 2023).

It is important in organizations to make sure that AI based learning and growth approaches emphasize on workforce diversity, rather than creating structural inequalities which are already present in society (Morandini et al., 2023). It is observed in literature that all employees does not experience GenAI equally. Some face more benefits, some face disadvantages and this changes workforce structuring, labor displacement, and career opportunities (Nica et al., 2024). Generative AI adoption can therefore create imbalance or inequalities in technological transformation of organizations (Acemoglu et al., 2022). That is why ethical concern is not a distinct issue concerning implementation, since even the overall organizational and labor market impacts of AI are themselves subject to the risk system surrounding adoption (Acemoglu & Restrepo, 2019).

Simultaneously, in the literature, GenAI is not strictly generating risk, but an entity characterized by an unresolved conflict between significant opportunities and threats that are equally significant. Generative AI is deified as one of the powerful solutions to complex problems, routine tasks, and helps in creating new types of value within organizations (Davenport & Mittal, 2023). Research in industries also indicates that its business value in the ability to streamline processes, make personalized decisions, and transform the decision-making process in organizations is quite context specific and may have the mentioned beneficial impact (Ooi et al., 2025). Its ability to enable design, forecasting, communication, and optimization is also associated with its rapid adoption by firms (Harreis et al., 2023). Strategically, Gen AI might support instead of substitute human decision-making and bring in opportunities to enhance organizational learning and performance (Gaessler & Piezunka, 2023).

In logistics, in particular, Gen AI will be capable of validating and visualizing supply chains, supporting a supplier evaluation, and pointing toward less risky sourcing strategies, showing that it can potentially have staggering capacities in all-encompassing and more transparent networks in the future (Wichmann et al., 2020). It also seems to be useful in the integration with IoT systems, creation of KPIs, and enhancement of supply chain visibility, which are all extremely important to logistics companies that demand quicker and more precise coordination (Frederico, 2023). However, such opportunities cannot be discussed without referring to threats due to the risk of increased reliance on opaque systems, faster responses, and decision-support offered by the same technology, which may rely on the wrong data and place more organizational risks unless implemented with proper human supervision and regulation (Kar et al., 2023).

2.8 Theoretical Foundation

This work is theoretically based on the socio-technical systems (STS) theory and punctuated socio-technical change (PSTC), which creates a comprehensive perspective to understand how Gen AI is restructuring workforces, organizational operations, and experiences of employees within logistics and supply chain sectors. These theories help to view technological change not as a onedimensional phenomenon, but as a multifaceted process of interaction between human agents, technologies, and organizations´ structures, precisely an area that is of the interest of this research.

2.8.1 Socio-Technical Systems (STS)

The theory of socio-technical systems (STS) was developed at Tavistock Institute when Trist and Bamforth showed that the performance of an organization is determined by the mutual dependence between the social and technical factors and not the efficiency of technology applied alone (Trist & Bamforth, 1951). Their analysis of coal mining systems revealed that the optimization of machinery without accounting the human work organization showed decreased productivity and dissatisfaction of the workers, establishing the main principle of joint optimization of social and technical subsystems (Trist & Bamforth, 1951). This was a change of technological deterministic approach where workers are not passive elements in systems but instead active subjects whose expertise, relationships and autonomy determine organizational results (Trist, 1981).

To develop on this background, STS theory views organizations as closed systems with interdependent components, which always remain in a state of interdependence with each other and with the external environment, and whether they are to be stable and effective, there must be an alignment (Bertalanffy, 1950). In this model, organizations are viewed as comprising two major subsystems, which are the technical subsystem and the social subsystem. The former comprises of tools, technologies, and processes employed in performing tasks (the technical subsystem), and the latter comprises of human actors, their skills, values, and relationships (Bostrom & Heinen, 1977). It is required that the subsystems in an organization attain alignment so that when this is not achieved, then results are inefficiency, resistance and poor results (Cherns, 1976).

The interplay between the technology, people, and organizational arrangements is also a primary mechanism in the STS theory since organizational systems consist of interrelated system components that respond to each other (Leavitt, 1965). The model by Leavitt (1965) further formalized this interaction by presenting four important elements of technology, tasks, structure and actors and showing that a change of one element in the system needs adjustments in the other in order to reach system equilibrium (Leavitt, 1965). In this definition, technology can be understood as the tools and systems through which work is done, the people can be understood as individuals and groups who interact with the use of these systems and the structure can be understood as the operational arrangements of organizations, like work processes, hierarchies, and patterns of communication (Morton, 1991). These are dynamically dependent elements, that is, technological innovation is dynamically dependent on work practices, organizational structures, human behavior, and institutional arrangements, which are also dependent on how technologies are being implemented and used (Bloomfield & Vurdubakis, 1994).

The advancement of the STS theory has generalized its use to the design of organizations and information systems (Mumford, 1983). STS was further elaborated by Mumford (2006) where a focus on the aspect of participative system design was presented, claiming that employees are expected to participate when designing and implementing technological systems reflect the human requirements and organizational objectives (Mumford, 2006). Her contribution made useful approaches, like the ETHICS approach, where she emphasizes that the key to successful implementation of a system lies in striking a balance between efficiency and maintaining the well-being and satisfaction of employees. This contribution is especially relevant to the discourse of the contemporary digital transformation where the acceptance and engagement of employees are vital to the success of new technologies (Mumford, 2006).

On the same note, Lyytinen & Newman (2008) further extended the STS theory to information systems through a connection of both socio-technical interactions and organizational change processes. Their contribution focused on the idea that the technological change was a process of complex, non-linear interaction between social and technical factors and discussed the notion of punctuated socio-technical change (PSTC), describing how organizations should go through the periods of stability and be broken by technological disruptiveness (Lyytinen & Newman, 2008). This school of thought supports the notion that socio-technical alignment does not exist as a constant phenomenon but, instead, changes over time as organizations are changing to meet the new technologies and environments.

Within the framework of this dissertation, which investigates the role of Gen AI in restructuring the workforce in logistics and supply chain sectors, the STS theory can be effectively used to thoroughly examine the effect of technological adoption on transforming organizational infrastructures (Dwivedi et al., 2023). Gen AI introduces a change in the technical subsystem, and it changes employee functions, necessary skills, and decision-making pattern, at the same time forcing the change in the organizational structures like workflows, coordination process, and patterns of communication (Dwivedi et al., 2023). In the STS perspective, adoption of Gen AI should thus be viewed as a system-level change, which entails interplay of technology, people, and structure, as opposed to a technical implementation (Orlikowski & Iacono, 2001).

In particular, the adoption of Gen AI reallocates the work between employees and AI systems and forms hybrid working conditions where employees engage, interpret, and authenticate AI-generated outputs (Brynjolfsson et al., 2023). This change demands acquisition of new competencies, job descriptions, and reorganization of business operations to facilitate a productive partnership between humans and AI. According to STS theory, realization of alignment between organizational structures, workforce capabilities and technological capabilities can be the key to successful accomplishment of this transformation because a misalignment can result into resistance, inefficiency and poor employee experience (Leonardi, 2011). Thus, in this investigation, STS theory has been utilized as a theoretical framework to address the role of generative AI in the transformation of the workforce in logistics through the identification of the interaction of technological systems, human actors, and organizational structures by identifying how alignment or misalignment between these elements shapes both organizational performance and employee outcomes (Dwivedi et al., 2023).

2.8.2 Punctuated Socio-Technical Change (PSTC)

Punctuated Socio-Technical Change (PSTC) offers a process-based understanding of how socio-technical systems evolve by non-linear and discontinuous changes, instead of gradual and predictable change (Lyytinen & Newman, 2008). Based on the wider idea of punctuated equilibrium, PSTC theorizes organizational systems as experiencing lengthy slow periods of relative stability, where the existing structures, practices and technologies are held in place, then brief periods of a disruptive change that radically redesigns the systems (Gersick, 1991; Tushman & Romanelli, 1985). In contrast to the linear approach to change, the PSTC emphasizes that change is a result of the existence of accumulated tensions and disintegrations within the socio-technical systems, especially between technological capabilities, human activities, and organizational designs (Lyytinen & Newman, 2008; Van De Ven & Poole, 1995).

In this context, information systems are conceived as part of wider socio-technical systems where technology, actors, tasks, and structures come to play in a dynamic interaction over an extended period, giving rise to both stability and change processes (Leonardi, 2011; Orlikowski & Iacono, 2001). PSTC further explains that change takes place in a series of interdependent levels, such as work systems, development environments, and organizational contexts where disturbance at one level can create a series of transformations on the other (Lyytinen & Newman, 2008). One of the main mechanisms that can be identified in this process is that socio-technical gaps emerge, i.e., when new technologies do not match the existing skills, workflow, or organizational structures, and create pressures of adapting or changing (Lyytinen & Newman, 2008; Majchrzak et al., 2000).

In the context of this study Gen AI can be perceived through the lens of a technological breakpoint that puts the current socio-technical work systems in logistics and supply chain organizations into a state of instability (Dwivedi et al., 2023). Gen AI brings in novel automation, decision support, and knowledge generation features, disruptive to established task structures, skills needs, and organizational processes that cause a lack of fit between technological infrastructure and current workforce models (Budhwar et al., 2023). These misalignments mean there are socio-technical gaps that initiate transformation processes, which demand organizations to redefine technology, people, and structure by introducing change in the workflows, reskilling, and redesigning of structure (Svahn et al., 2017).

This disruption and realignment directly result in the workforce transformation outcomes, such as changes in task composition, introduction of new skill needs, and transformation of organizational structures, which align with the main dimensions of this research (Hinings et al., 2018). According to PSTC, these types of changes do not occur in an evenly spread manner or in a linear relative manner, but the changes are uneven and differ among organizations based on their effectiveness in responding to new socio-technical dimensions, with certain ones adapting gradually and others with a more radical restructuring (Lyytinen and Newman, 2008). Moreover, such changes are not only structural but also impact the experiences of employees since rapid and disruptive alterations in work systems can contribute to the perceptions of workload, job roles, and overall influence of AI on working practices (Dwivedi et al., 2023).

Thus, PSTC is considered as a supplement to the socio-technical systems theory because this perspective offers a dynamic and process-focused lens through which we can understand generative AI as not just a technological innovation, but as a source of disruptive change that generates and outlines complex socio-technical changes in logistics organizations (Leonardi, 2011). PSTC allows the study to imagine the process of workforce transformation in AI-enabled environments, and conceptualizing GenAI as a discontinuous event contributing to various transformations occurring in the whole system, allows the exploration of the phenomenon of cascading effects stemming out of disruptive technology changes on any given task, skills, organization structure, and experience of an employee, so that the study provides a well-rounded explanation of how workforce change emerges in AI-enabled settings (Dwivedi et al., 2023).

2.9 Conceptual Framework

Based on the theoretical foundations of socio-technical systems (STS) and punctuated socio-technical change (PSTC), this study formulates Gen AI as a technological catalyst which brings change to the socio-technical work systems of logistics organizations (Dwivedi et al., 2023). Under an STS approach, organizations are a system of interdependent constituents, such as technology, tasks, actors, and structure, the compatibility of which specifies the effectiveness and performance of systems (Bostrom & Heinen, 1977; Orlikowski & Iacono, 2001). GenAI introduction is a big change in the technological part of this system, as it alters the way work is performed or decisions are made, and how work is coordinated within the structures of organizations (Brynjolfsson et al., 2023).

In this setup, Gen AI disturbs the already established alignments formed between the technology, people, and the organization structures, leaving new technological capabilities and prevailing workforce skills, workflow, and institutional arrangements (Budhwar et al., 2023). These disturbances can be viewed in the context of the PSTC, which goes on to state that the processes of organization change in a non-linear manner with periods of stability preceding phases of disruptive change (Gersick, 1991; Lyytinen & Newman, 2008). Here Gen AI becomes an episodic process that induces socio-technical gaps that cause the need to change and restructure a system (Tushman & Romanelli, 1985).

With these socio-technical gaps appearing, organizations reorganize their systems through changes in tasks, skills, and organizational structures, which result in workforce transformation outcomes that are both technologically and organizationally adaptive (Hinings et al., 2018; Svahn et al., 2017). When GenAI is adopted organizations not only add a new technology but workflows are divided among technology and humans. Employees also need new skills and changes in coordination and work processes are observed (Brynjolfsson et al., 2023). According to STS, these changes are adaptations within the socio-technical framework, and according to PSTC view these are reactions to the disruptive change events that reform the system configurations over time (Leonardi, 2011; Lyytinen & Newman, 2008).

Moreover, these changes go way beyond structural and functional shifts to impact employee experiences including how they view their job roles, the amount of work to do and the overall impact of AI adoption in the working environment (Dwivedi et al., 2023). According to PSTC, these impacts are non-uniform since the level and character of change vary depending on how well organizations cope with socio-technical gaps and deal with disruptive technological change (Lyytinen & Newman, 2008). As a result, organizations may exhibit different outcomes of transformation based on their different capabilities, resources, and readiness, highlighting the need to look at both structure and human aspect of change (Hinings et al., 2018).

In this way, GenAI can be incorporated into the conceptual framework (check figure 1) of the present study as a technological trigger, and STS can serve as the system-level lens through which the interactions among technology, people, and structure should be interpreted, and PSTC can explain how disruption results in transformation (Dwivedi et al., 2023). In this context, workforce change is theorized to be a pivotal outcome, which thus is a change in tasks, skills, organizational structures, and employee experience (Brynjolfsson et al., 2023).

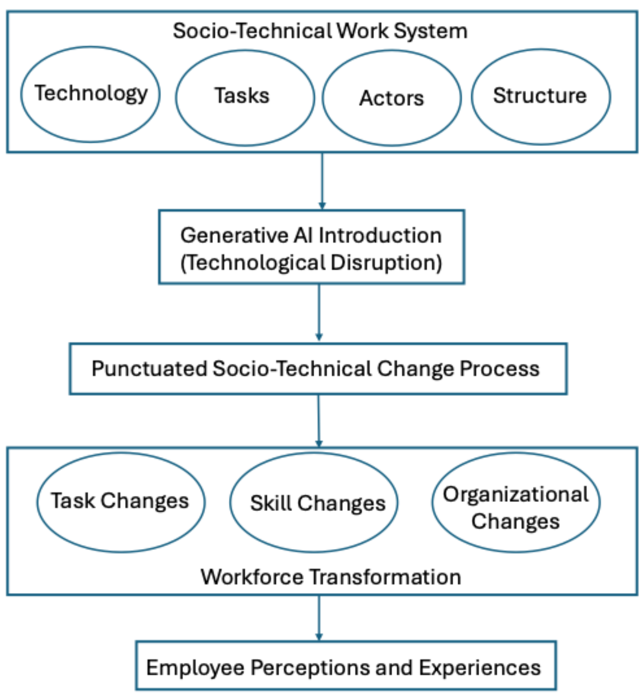

Figure 1. Conceptual Framework

3 Methodology

This chapter introduces the research methods of this dissertation in explaining why this approach was chosen, data collection processes, data preparation, and data analysis. The measures of reliability and validity that had been adopted to assure the research process were also explained in the chapter.

3.1 Research Design

The present research is based on a qualitative research design to examine the socio-economic impact of Gen AI on transforming the workforce in the logistics and supply chain sectors in Finland, particularly in Helsinki, Tampere, and Vaasa cities. The choice of a qualitative approach is explained by the intention of the study to know how employees think, experience, and interpret the change as a result of the implementation of Gen AI, not assessing a predefined set of variables with a statistical approach (Creswell & Poth, 2016; Flick, 2018). Qualitative research is appropriate to investigate complicated phenomena in an organization when the views, experiences, and contextual meanings of participants are in the center of interest in the research issue (Creswell & Poth, 2016).

This paper follows an abductive process. Depending on the way the theory and data are applied in the process of conducting a research, qualitative research comprises inductive, deductive, or abductive reasoning (Mantere & Ketokivi, 2013). Abductive reasoning is suitable in this work as it entails both forward and backward movement between empirical data of interviews on one hand and theoretical basis of STS as well as PSTC. Abductive research allows the researcher to seek explanations to existing theoretical ideas on the basis of the empirical observations at the same time being adaptable to unexpected patterns as a result of the data (Hurley et al., 2021; Rinehart, 2021; Timmermans & Tavory, 2012).

The qualitative abductive design fits in this research since the study aims at the investigation of the impact of Gen AI on workforce transformation by exploring how the Gen AI impacts the workforce by altering the tasks and skills of the workforce, transforming organizational workings, and transforming the workforce experiences. STS theory assists in examining the interaction among technology, people, tasks and organizational structure whereas PSTC is useful in revealing how non-linear changes can be created in social-technical systems due to technological disruption (Bostrom & Heinen, 1977; Lyytinen & Newman, 2008; Trist & Bamforth, 1951). That is why the chosen research design enables the study to relate employee experiences upon the uptake of Gen AI to the wider theoretical knowledge of socio-technical change.

Semi-structured interviews were chosen as the main data collection method. The approach is appropriate since the participants can share their perceptions and experiences using their own words, besides providing the researcher the opportunity to look into certain problems related to the research objectives (Flick, 2018; Kvale & Brinkmann, 2009). As this research revolves around employee perception and experience with Generative AI in logistics companies, semi-structured interviews were flexible enough to consider how these participants interpreted change in work practices, skills needed, workload, decision making, and how the organization adapted to the change.

3.2 Data Collection

This research employed semi-structured interviews with the employees and managers of the organization related to the logistics and supply chain sector as a source of primary data. The interviews were focused on the participants and the exploration of their experience and perception of the implementation of Generative AI in workplaces, its impact on work operations, skills that need to be developed, decision-making process, workload, motivation, opportunities, risks, and future workforce reflection. This methodology made it possible to gather rich empirical data that could be directly related to research questions and the theoretical framework of the study.

The data collection was based on the purposive method of sampling. Qualitative research often involves purposive sampling because it enables the selection of participants who have some knowledge and practical experience concerning the topic of the research (Emmel, 2013; Flick, 2018; Palinkas et al., 2015). Participants in this research were chosen depending on their professional involvement within the logistics and supply chain related work environments as well as their knowledge of the usage, application, or awareness of Gen AI technologies in organizations. The sample also contained participants with different professional roles, education level and work experience, which substantiated the gathering of diverse points of view concerning the workforce change and AI implementation in the logistics organizations.

In total, seven semi-structured interviews took place with the participants representing operational, administrative, and managerial positions. The participants varied in terms of age group, responsibilities, and duration of employment. The average length of the interview was between 30-45 minutes. The research was conducted using identifiers like R1, R2, R3, etc. to keep the participants confidential and anonymous. Involvement in the research was optional, and all the participants were informed of the aim of the research prior to the interviews. The interviews were recorded and informed consent was obtained before the recording. The data was collected until thematic saturation was achieved, i.e. repetition of patterns and similarity of themes were found in the answers of the participants and no new meaningful information was obtained. Interviews were stopped to provide fresh insights or themes when the data collected were already sufficient (7 interviews) and thus they were saturated (Francis et al., 2010; Guest et al., 2006). When coding, the author reviewed the data all the time depending on the applicability of the topic. New interviews were watchfully observed to bring in new themes or insights. After 5 interviews, no additional themes were being developed and the remaining interviews supported previous themes, which supported the viability of the sample size (Saunders et al., 2018).

Table 1 below shows the demographic profile of the participants:

Participant ID	Age	Gender	Profession/ Role	Highest Qualification	Sector	Duration of Employment
R1	60+	Male	Supply Chain Manager	Bachelor's Degree	Private sector	21 years
R2	40-49	Male	Logistics Manager	Ph.D	Private sector	15 months
R3	30-39	Male	Business Owner	Ph.D	Private sector	11 years
R4	40-49	Male	Integration Manager	Bachelor's Degree	Private sector	16 years
R5	40-49	Male	Logistics Manager	Master's Degree	Government sector	4 months
R6	50-59	Male	Logistics Architect	Bachelor's Degree	Private sector	26 years
R7	30-39	Male	Logistics specialist	Master's Degree	Private sector	7 years

Table 1. Demographics

Online interviews were performed using a digital communication platform (Microsoft Teams), which allowed participants to attend scheduled interviews with flexibility, irrespective of their location. Also, online interviews allowed accessibility and good coordination in the process of collecting data. Interviews were performed in English language and recorded with the consent of the participants to secure proper preservation of responses in order to render correct transcription and analysis.

The interview questions were created according to the research objectives and theoretical background of the study. Questions addressed how participants use and perceive Gen AI tools at work, how their work activities and work responsibilities change, new skills needed, decision-making, communication patterns, and perceived opportunities and risks of using AI. The interview design itself was also congruent with the Socio-Technical Systems (STS) and Punctuated socio-technical Change (PSTC) frameworks since the questions touched upon the interaction between the technology, organizational structures, work practices, adaptation processes and transformation of the workforce.

After the interviews were completed, the recordings were transcribed and prepared for analysis. Reviewing was done to make sure that throughout the process of transcription, the intended meanings of the participants were not lost. The data were later imported to NVivo to be coded and analyzed through themes. The process helped to systematize the interview data and helped to detect the common themes, patterns, and relationships in answers provided by participants.

3.2.1 Reliability and Validity

To enhance the reliability and validity of this study, several measures were used. All the interviews were recorded and transcribed carefully so that analysis can be conducted as close to the actual words of the participants as possible. This is significant in a qualitative study since precise transcription facilitates familiarization with the information and minimizes chances of interpretation error (Guest et al., 2012). The researcher also reread the transcripts several times prior to coding to get used to the responses of participants as well as to see the preliminary patterns in the data. Moreover, the uniformity of the semi-structured interview guide enhanced reliability. Even though the interview format provided flexibility, similar overall questions were used throughout the interviews to make sure that all participants focused on similar issues. This helped us to ensure consistency in the process of data collection while still allowing participants to explain their experiences in detail (Flick, 2018; Kvale & Brinkmann, 2009).

The use of NVivo also contributed to the reliability, as this facilitated systematic coding, organization and retrieval of different interview information. The codes were made through an iterative process and codes that shared similarities were grouped into larger themes. This was used to keep a uniformity in coding decisions and enhanced transparency in the analysis process. In qualitative research, it is significant to have a clear coding structure as it enables the researcher to follow how themes emerge out of the information (Braun & Clarke, 2006).

The abductive movement between the empirical data and theory was instrumental in supporting the validity. Results were explained within the framework of STS and PSTC, as well as grounded with participants' interview responses. This contributed to the fact that the analysis was not done on mere theoretical assumptions but it was also backed by empirical data. The validity in abductive analysis enables the scholar to compare growing outcomes against the available theoretical descriptions and refocus the interpretations to the theory (Rinehart, 2021; Timmermans & Tavory, 2012). Another method the study employed to instill trustworthiness was the rich contextual description. Professional role of participants and experience, as well as their statements in the interview, were taken into account in interpreting the findings. Contextual detail enables readers to grasp the context of the study and determine whether the results can be applicable in similar contexts (Creswell & Poth, 2016; Lincoln et al., 1985). The results chapter also contained direct quotes of respondents to substantiate the interpretations and demonstrate how results were related to the responses of participants.

3.3 Data Analysis

Abductive thematic analysis was used to analyze the data. Thematic analysis is a qualitative approach, which is popular in recognizing, systematizing, and explaining patterns in interview data (Braun & Clarke, 2006). The thematic analysis was suitable in this study to find the most prominent themes connected to workforce transformation following adoption of Generative AI such as modification in work, skills, decision making, adaptation to organizational change, opportunities, risks, and employee perceptions. The reasoning was abductive since the research approach was an integration of theoretical advice and empirical openness. A theoretical framework based on STS and PSTC, particularly the technology, tasks, actors, structure, socio-technical alignment, disruption and adaptation concepts were used as the initial investigation (Bostrom & Heinen, 1977; Lyytinen & Newman, 2008; Trist & Bamforth, 1951). Meanwhile, the researcher was willing to incorporate new patterns out of interview data, including AI as a support tool, surface-level use, human validation, data organization, route optimization, and employee risk perceptions.

The familiarization with the data was the initial phase of the analysis. Interview transcripts were read several times to understand the overall meaning of participants' responses. At this point, preliminary notes were taken as to recurrent ideas, significant statements, and potential patterns. The thematic analysis process also includes familiarization as a significant preliminary step since it involves the researcher becoming immersed in the data, prior to engaging in formal coding (Braun & Clarke, 2006; Guest et al., 2012). The second phase entailed coding of interview data in NVivo. Coding was done based on the identification of meaningful statements with respect to the research questions and linking it to a specific code. The coding procedure was not different from the words of the participants to ensure that important meanings were not lost. First codes had sections like AI for documentation, automation of tasks, reduction of manual tasks, faster decision-making, need to verify AI outputs, human control remains important, training and courses, early-stage adoption, and possible workforce reduction.

The third step was reviewing and grouping codes into general themes. The similar codes were grouped together into higher-level themes using conceptual similarity and research objectives. Themes that emerged during this process include AI-inspired change in work organization, how employees view AI, human-AI cooperation and decision support, opportunities and threats, and organizational response to Generative AI. These themes were created through similarity of the coded data among interviews and verification of whether each theme was an apparent pattern in the data set. The fourth step was to make sense of the themes using the theoretical framework. The interaction between Generative AI and human actors, tasks and organizational structures were explained using STS theory, and the understanding of how AI adoption brings disruption, gaps and gradual realignment to logistics and supply chain organizations was explained using PSTC (Leavitt, 1965; Lyytinen & Newman, 2008; Mumford, 2006). Such abductive movement between data and theory allowed the study to come up with a theoretically informed understanding of workforce transformation. Lastly, the results chapter also presented the themes with direct quotations cited by the respondents. Quotations were used to aid in establishing the credibility of the findings. The thematic interpretation and theoretical explanation thus complemented the participant evidence to provide answers to the research questions of the study.

4 Results

This part comprises of the results of the dissertation regarding the abductive method of thematic analysis (check figure 2), combined with interview data and themes, with the support of STS and PSTC. An abductive approach has been followed, meaning that results are generated by going back and forth between data and theory and findings were based on theoretical background (Timmermans & Tavory, 2012). This process was followed throughout the analysis. In total, 5 final themes were developed in NVivo which also included subthemes and codebook (see Appendix 2), which mentions correlated information of participants´ data. The results of the dissertation are discussed as follows:

4.1 AI-Driven Transformation of Work Processes

The findings indicated that Generative AI has already begun to reshape work processes of logistics and supply chain organizations by diminishing manual work and enhancing operational efficiency as well as providing more structured workflows. Throughout the interviews, the respondents shared the general view of AI as a solution that makes the work processes easier, faster, and more informative. The results correspond with earlier research that suggested that Generative AI can help automate workflows, optimize processes, and increase flexibility in operations in an organizational setting (Dwivedi et al., 2023; Wamba et al., 2023). From STS view, it is observed that workforce and technological collaboration makes the work processes efficient (Bostrom & Heinen, 1977; Leavitt, 1965).

A common pattern that was most prevalent in the interviews was the decline of manual operational activities. Respondents elaborated that previously, tasks associated with logistics involved a lot of manual coordinating, physical participation, or lengthy information retrieval operations. According to participant R1, to streamline logistics operations, the SAP systems required employees to manually search information before the system could be adopted since all planned operations required a user to search and coordinate with external partners to obtain the information they needed. Participant R1 also stated that “Before AI we were deep diving into our own SAP systems to get the data... Also checking with external cooperators to get the needed data to optimize logistics." The respondent went on to say that AI facilitates these activities with a quicker analysis and information retrieval and stated that "Now, in this new world of AI, we are getting more analysis and data with AI help and support." Similarly, participant R3 explained that route planning had previously involved physical examination and the collection of data by hand, saying that "If I look back five years when we used to make routes, you had to be physically on the route and collect all the information by yourself." Nevertheless, the respondent said that the systems powered by AI have made these activities easier by saying that "Now, with these new tools, you just give a command… and it can do the work". These results imply that AI is gradually mechanizing repetitive and data-heavy tasks of logistics and supply chain processes. It also supports previous studies which explain that Gen AI technologies enhance operations automation and process optimization in the logistics and supply chain setting (Kmiecik & Skórnóg, 2025; Ooi et al., 2025). From STS view, manual activities are declining and with technological advancements the task structures and work practices are reorganizing (Bostrom & Heinen, 1977; Leavitt, 1965).

The other significant observation is related to the improvements in workflow and efficiency. Respondents pointed out that GenAI systems played a big role in minimizing the time taken to perform both operational and administrative functions. R3 said that "It saves about like three months of work, now it takes only a couple of days." Similarly, R1 explained that "I think mostly it has just helped me get things done faster." R2 also mentioned "Before that, it took weeks to prepare it properly, translate it correctly, and decide where to place it.. In less than one minute, they are getting the proper layout." R2 additionally stated that "our working process definitely started to become easier with the use of AI tools because it gives us more flexibility, more possibilities, and more opportunities." These results point to the fact that the main perceptions of Generative AI among employees are based on its ability as a tool for enhancing productivity to optimize the work process and decrease the time wasted within the operations. This finding also aligns with STS view that technology can improve efficiency of tasks and it reshapes work processes in organizations (Bostrom & Heinen, 1977; Trist & Bamforth, 1951). It is consistent with previous reports that Generative AI positively correlates with productivity through quicker administrative and analytical processes (Dwivedi et al., 2023; Harreis et al., 2023).

The findings also demonstrated that the AI adoption leads to more organized organizational procedures and coordination of the working process. Some of the respondents described that the introduction of AI prompts companies to organize the workflow, communication patterns, and information organization systematically. Respondent R6 explained that “We need to take all bits and pieces and put them into a more structured and governed working model.” Similarly, R5 emphasized that organizations increasingly need structured data management practices to support AI systems, explaining that “The biggest change concerns how data is stored and structured to be accessible for AI.” Respondent R4 further mentioned that it is visible that many employees are using Gen AI in work by stating that “I can definitely see if somebody has used AI to compile a summary or prepare an internal email with AI.” These findings indicate that Gen AI implementation does not solely alter the work of individuals but also the overall organizational coordination and information management practices (Sharma, 2023; Wamba et al., 2023). On a socio-technical systems dimension, this shows how the interaction in between technical and social aspects reshapes organizational structures and processes in the working environment by using technological systems (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

The findings also revealed that Generative AI is becoming actively incorporated in the basic logistics and supply chain processes like tracking shipments, or verifying customs, and operational planning. R2 had clarified that Gen AI assisted solutions enhance shipment visibility and logistics coordination, saying that stating that “AI tools provide much more detailed shipment tracking”. In the same way, R4 mentioned about utilizing AI in customary checks, saying that “Whatever the person is approving has been produced by AI.” R3 also articulated that AI is used more in route planning and the generation of operational instructions. These results show that the application of AI is slowly diversifying to the areas of operation in the logistics side of operations instead of doing administrative tasks. This confirms earlier reports that AI technologies contribute more to the coordination, planning, forecasting, and optimization of operations in the logistics and supply chain (Cadden et al., 2022; Lei et al., 2024). With regards to PSTC, Gen AI is involved in main logistics operations like tracking of shipments or verifying custom procedures this indicates how technology adoption has reshaped the work activities within logistics organizations (Lyytinen & Newman, 2008).

Besides the transformation of operational processes, the findings also indicate that Generative AI is also shaping the responsibilities and skills requirements. Respondents stated that employees are now in need of more extensive knowledge, digital literacy, and the capability to understand AI generated outputs. R5 mentioned that "The required skill level rises. They need to be able to see the big picture, understand processes and be able to streamline them." The respondent went further to elaborate how work in the future is becoming more strategic, stating that "Work will be less operational and more strategic." Similarly, R4 described that "Gen AI is able to produce a summary of the easy things and lets me focus on the most difficult ones." These results imply that the role of AI in employee responsibilities is slowly transforming from repetitive operational execution toward supervision, interpretation, and strategic coordination tasks (Acemoglu & Restrepo, 2019; Autor, 2015; Awad & Martín-Rojas, 2024). From STS perspective, employee responsibilities and skills are also altered by Gen AI adoption alongside with technological change in organizational system (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

The results indicate that Gen AI is aiding a paradigm shift in the current transformation of work processes in logistics and supply chain organizations through automation, the enhancement of efficiency, the reorganization of workflows, and the redistribution of operational tasks. Instead of completely eliminating employees and workers, AI now seems to serve at least as a support tool that leaves the coordination of the operations simpler, with the repetitive tasks being simplified. In socio-technical systems lens, the findings reveal the restructuring of organizational tasks, organization, and employee position under the influence of technological systems through the ongoing interplay of social and technical factors (Bostrom & Heinen, 1977; Trist & Bamforth, 1951). Simultaneously, the findings also capture the aspects of punctuated socio-technical change (PSTC) since organizations seem to be leaving progressive systems of the traditional manual operations behind and entering the realm of AI-assisted and digitally coordinated workplaces (Lyytinen & Newman, 2008).

4.2 Employee Attitudes towards AI

The findings revealed that the perception towards Generative AI was mostly positive amongst employees. The overall characterization of AI by respondents was that of a valuable auxiliary tool that ensures better efficiency in the workplace, increased flexibility, and provides additional opportunities to carry out tasks. Meanwhile, the results also indicate that employee perceptions also depend on several factors that encompass the organizational culture, personal attitudes towards technology, security issues, and insecurity about future job impacts. Such results provide insights that support the earlier literature that Gen AI based perceptions depend on both the technological potential and the organizational environment, trust, and socio-technical factors under which AI is adopted (Bankins et al., 2024; Budhwar et al., 2023).

One of the major findings was that the employees usually perceive Gen AI as an aid resource that positively influences the working process and productivity. Respondent R1 explained that “I think mostly it has just helped me get things done faster. I would say almost everything is positive.” Similarly, R5 stated that “Yes. I see them positively and expect them to be good assistant in future.” R2 also stated that “It is like getting one extra or additional team member. This AI is always with you, and you can always ask it to get some results.” These results indicate that the main perception of the employees is Gen AI as a supportive system and not as a substitute for human work. This reinforces previous sources that suggest that employees are more inclined to embrace AI technologies when they believe that they do not replace but improve the abilities of people (Brynjolfsson et al., 2023; Jarrahi, 2018). These findings demonstrate the concept of technological systems with markers of socio-technical systems (STS), where human actors and technological systems do not interact directly but instead depend on each other (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

The findings also revealed the fact that a significant number of employees were interested, excited and personally wondered about AI technologies. Some of the respondents had characterized AI adoption to be inspirational and thought provoking. R6 elaborated that “I feel excited, even though I told my superior that I might be doing things that could get me out of work. But it’s so exciting, so I can’t stop myself.” On the same note, R1 explained that motivation increases because “you get more information. a clearer picture and faster results.” R2 termed AI use as “…good motivation to use these AI tools in the future as well”. These findings suggest that the implementation of GenAI can enhance employee engagement and motivation in cases when employees think that AI can enhance their functioning and assist them in producing better results at work. This is in line with earlier studies which hold that AI assisted workspaces have the potential to boost intrinsic motivation as they allow employees to prioritize more meaningful and value adding tasks (Omri et al., 2025; Szeszák et al., 2025). These findings supports STS perspective that Gen AI is more like supporting employees in their tasks rather than substituting them, highlighting appropriate alignment of technology and humans (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

Nevertheless, despite the mostly positive perceptions of the employees, the results showed the existence of various ways of resistance and uncertainty towards the adoption of AI. But the resistance was usually characterized as moderate but not severe. Respondent R1 described that “If you are open to new things, it’s easy and even exciting. But some people may see it as a risk.” In a similar vein, R6 outlined how AI usage can socially separate interested and non-interested employees, explaining that less interested employees might be opposed to any discussion on adoption of AI since “you might only get resistance from them”. These results indicate that the uptake of AI is influenced by personal attitudes, readiness for technology adoption, and organizational social processes as discussed in previous literature that acceptance of AI depends upon factors such as trust, perceived usefulness, organizational support, and attitudes toward technological change (Bankins et al., 2024; Budhwar et al., 2023). This is a manifestation of the STS theory according to which human behavior, organizational culture and interaction rather than purely technical capabilities (Leonardi, 2011; Mumford, 2006).

The findings also indicated that there were employees who correlated AI adoption with job and workforce security. Respondent R4 mentioned that “there is an assumption that if they use it, they will lose part of their work to AI”. On the same note, R6 claimed that “if I don’t add value, then I don’t really have a role here”. These results indicate that on the one side, employees tend to have a positive attitude towards AI, on the other hand, they realize that AI will change the future job performance and work organization. It reflects past studies that technological use has generated opportunities and fears related to employment security and workforce restructuring (Acemoglu and Restrepo, 2019; Nica et al., 2024). These issues may be the responses to disruptive technological change in a punctuated socio-technical change (PSTC) perspective, when organizations feel uncertain and socio technically misaligned when faced with swiftly shifting change (Lyytinen & Newman, 2008).

The other significant discovery was related to organizational and security issues related to the adoption of Gen AI. Some of the respondents described how organizational hesitation and data protection issues were adoption barriers rather than the employees’ direct resistance. R4 stated that “The slowest adoption will come because of security concerns, not because people are resisting adoption”. The respondent also elaborated that organizations would only comfortably implement AI systems when they are “…100% sure that the AI database consuming the information will not leak it outside”. Such results indicate that the attitude of workers towards AI is directly related to the wider issue of organizational trust and governance. It validates earlier findings that note that trust, transparency, and data governance are fundamental drivers of AI acceptance in organizations (Dwivedi et al., 2023; Khogali & Mekid, 2023). This is also a mirror of how technological adoption is contingent on the correspondence between technical systems and organizational structures with the trust relationships between humans as seen in an STS perspective (Bostrom & Heinen, 1977).

It was also found that the perceptions of AI vary according to the organizational roles, familiarity on technology, and situations of practical work. R6 explained that “It depends a lot on how people work, what they are used to, what tools they have”. Likewise, R1 mentioned that openness to AI is based on personality. These results suggest that there is no standard perception of AI among employees in organizations, but rather it depends on the practices of work, experience, and culture of the organizations. This goes in line with the socio-technical systems theory that argues that technological systems have varying interactions with organizational routines, identity of employees, and the social structures (Leavitt, 1965; Smiderle et al., 2020).

In general, the results indicate that the workforce working in logistics in supply chain organizations tend to have a positive perception of Gen AI, especially in terms of productivity, flexibility, and better work support. The perceptions of the employees are, however, also influenced by fears of the organizational security, future implications of the workforce and the level of openness to the technological change. These results confirm the socio-technical systems theory and the punctuated socio-technical change theory as they show that Gen AI adoption is not merely a technical process, but also a social and an organizational change that transforms employee attitude, work relationship and future work perceptions (Lyytinen & Newman, 2008; Trist & Bamforth, 1951).

4.3 Collaboration between humans and AI and support of decisions

The findings indicated that Gen AI is becoming more of a supporting system in logistics and supply chain organizations that can support rather than replace human decision-making. Throughout the interviews, all respondents referred to the concept of AI as something that could help employees to generate information, facilitate analysis, enhance visibility, and access knowledge faster, but the ultimate task and decision-making should be taken by human actors. These results are consistent with the past literature which indicates that Gen AI plays a role in the hybrid intelligence where human skill is supplemented with AI assisted systems instead of being replaced completely (Brynjolfsson et al., 2023; Jarrahi, 2018). In a socio-technical systems (STS) approach, this illustrates how organizational performance is becoming more reliant upon interaction and fit between human actors and technological systems as opposed to technological automation as an isolated approach to organizational performance (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

Among the patterns established during the interviews was the use of AI as a decision support tool. Respondents described how Gen AI systems offer extra information, overviews, analysis, and the working insight that enhance the effectiveness and speed of the decision-making process. R1 described “during discussions or processes we first think ourselves how it could be, and then we use AI to get more information”. The respondent added on this “That gives us better background for decision-making”. On the same note, R4 said that “AI help to pinpoint the exact things the company wants to focus on… while also allowing employees to focus only on the most relevant things and then just review the less relevant ones”. These results imply that Gen AI systems can become analytical assistants that contribute to greater organizational awareness and facilitate decision-making process. It also justifies prior studies, which claim that AI technologies increase the quality of decisions made by organizations due to their efficiency in processing information rapidly, analyzing situations, and offering predictions in complicated settings (Kaplan, 2019; Wamba et al., 2023). Considering STS view, Gen AI provides supports in decision making keeping the interpretation and judgemental responsibilities to humans (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

The results also revealed that the respondents strongly believed that human supervision was always important in the process of making decisions with the support of AI. Employees insisted that human agents should still be in charge of the final assessment and approval, when Gen AI outputs were found to be of great use. Respondent R1explained that “you still have to check if it is really okay.” Similarly, R3 stated that “we still have to check that everything is correct.” R4 also emphasized that “It still needs a person to make the call and do the necessary changes,” even when AI performs analysis and generates recommendations. These findings show that employees do not believe that AI is completely autonomous and fully trustworthy without human control. Rather, human-AI interaction seems to work by providing the same interaction through which AI produces outputs and humans interpret, validate, and accept them. It is in accordance with the previous works that believe that successful human and AI collaboration requires preserving human judgment, contextual awareness, and responsibility in decision-making systems (Jarrahi, 2018; Raisch & Krakowski, 2021). In the view of STS, this is the way of the principle that technological systems do not dominate but support workforce in organizational processes (Cherns, 1976; Mumford, 2006).

Another notable discovery was the increasing use of AI in information and analytical work. A number of respondents outlined how AI systems assist in data retrieval, data summarization and data analysis of operations in various logistics and supply chain functions. R1 explained that "we use AI to help us cover the information needed" during negotiations with companies. Similarly, R4 stated that "I use it to analyze the specific information that I ask for." The respondent further explained that internal AI systems are "focused on analyzing information and then providing a summary of actions." R6 also described AI as a "sparring partner" that provides "much more background information". These results evidence that AI-based systems are gradually becoming cognitive support systems that can boost the level of analytics and access to operational knowledge in employees. This is in favor of prior studies that suggest that Gen AI adds to knowledge-intensive work, along with synthesizing information, content generation and analytical reasoning in organizational contexts (Dwivedi et al., 2023; Feuerriegel et al., 2024). It also supports STS view, the interaction between employees and technological systems is getting stronger in analytical capabilities, increasing access to information, and providing required knowledge to complete tasks (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

The results also revealed that AI is becoming an important part of the operational coordination and execution of processes in logistics and supply chain organizations. Respondent R4 explained about the transformation of customs verification procedures under the incorporation of AI, stating, "whatever the person is approving has been produced by AI." Similarly, respondent R3 explained that route planning and operational instruction generation can now be completed "through the system more automatically and then verify it". These results indicate that Gen AI is slowly changing the working processes by automating analytical and operational tasks that involve a lot of coordination and retaining human review responsibilities. It can be correlated with the literature that suggests that AI systems will be used to coordinate and plan logistics and operations monitoring in the supply-chain setting more in the future (Cadden et al., 2022; Lei et al., 2024). In the PSTC view, consequently, the developments can be viewed as socio-technical disruptions that transform task design and redistribute human and intelligent system duties (Lyytinen & Newman, 2008).

Meanwhile, the respondents pointed out that Gen AI ought to be a facilitating technology but not an autonomous authority. Respondent R1 mentioned that “AI should be more like a support tool for us.” Similarly, R6 explained that “AI should not be the master, but the servant.” These results are indicative of a profound belief that technological systems can add value to human work, but not take over the decision-making processes in an organization (Leavitt, 1965; Mumford, 2006). This asserts the socio technical systems theory that asserts that the technological systems should be in line with human needs, organizational objectives and the system of employee control to ensure that these systems perform effectively in organizations (Leavitt, 1965; Mumford, 2006).

The findings also indicated issues with transparency and restrictions of outputs in Gen AI. Respondents have accepted that AI systems cannot always be trusted and can deliver the wrong or incomplete information. R6 described AI as “more like a black box” where “you can’t always see where it is fundamentally wrong.” Similarly, R1 explained that AI-generated information “is not always correct.” This indicates that, as much as AI provides a better analysis and decision making support, workers are still worried about being over-reliant on Gen AI outcomes. This reflects earlier research on issues about explainability, transparency, and trust of AI supported organizational systems (Ferrer et al., 2021; Khogali & Mekid, 2023). These issues are socio-technical tensions as seen through the prism of PSTC whereby sociocultural organizations are trying to adopt high technology into current work processes while ensuring that their operations remain reliable and accountable (Lyytinen & Newman, 2008).

Altogether, the results indicate that Gen AI is becoming a major determinant of collaborative work settings where people and Gen AI systems collaborate to provide organizational decision-making and operational coordination. The use of Gen AI is not intended to substitute the employees, but rather act as an assistant that improves the analytical potential, information accessibility, and visibility of operations as the ultimate decision-making and responsibility remain with the humans. The results justify socio-technical systems theory and punctuated socio-technical change theory in the sense that they indicate that the adoption of Gen AI is always characterized by a continuous interaction among the technological systems, the organizational structures, and decision making practices implemented by workforces (Lyytinen & Newman, 2008; Trist & Bamforth, 1951).

4.4 Opportunities and Risks of Generative AI

The perceptions of Gen AI varied greatly between employees and managers in logistics and supply chain organizations, who tended to see it as an important promise in terms of efficiency, organizational operation, and growth in the future. Simultaneously, some of the risks linked to the adoption of Gen AI were also indicated by respondents, including the substantial implementation of AI systems in the field and its associated effects on workers, polarization of skills, data safety, excess dependence, and lack of understanding of the future AI implications. Such results back up the existing body of literature which argues that Gen AI presents both innovation opportunities and productivity alongside with creating social-economic and organizational risks (Davenport & Mittal, 2023; Dwivedi et al., 2023). In terms of PSTC, such findings are mirrored by the fact that disruptive technologies create transformatory gains as well as socio-technical strains during their organizational adaptation phases (Lyytinen & Newman, 2008).

According to the respondents, one of the most frequently encountered opportunities has been better access to information and a greater visibility of operations. A number of respondents said that the use of Gen AI allows facilitating easier access to information, processing and use in company processes. Respondent R1 stated that “It makes it easier to get information that was hidden.” Similarly, R2 explained that AI tools “give us more flexibility, more possibilities, and more opportunities.” The respondent further stated that AI tools create opportunities because “they give us different options.” These results indicate that Generative AI increases access to organizational knowledge and promotes more effective information processing in logistics and supply chain settings. This corresponds to the literature that suggests that AI technologies increase organizational responsiveness and coordination, in addition to greater readability of the data and integration of information, which enhances their accessibility (Ooi et al., 2025; Wamba et al., 2023). This supports STS perspective as generative AI is improving employees’ access, interpret, utilize information that is strengthening organizational knowledge flows, hence, providing well informed work practices and decision making process (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

Several respondents also outlined future opportunities related to the optimization of operations and visibility of real-time logistics. According to R2, the existing organizational logistics procedures are still associated with uncertainty since organizations do not have real-time shipment visibility. The respondent explained that “at some point, AI tools will give us the possibility in real time to check where the truck is.” The respondent further described AI as potentially becoming “my own eyes on the road.” These results suggest that Gen AI systems will be utilized by employees to enhance visibility, coordination, and tracking on logistics networks. This is in line with the earlier research that Gen AI technologies can enhance supply chain coordination, route optimization, and real-time operations monitoring in the complicated logistics systems (Lei et al., 2024; Srivastava et al., 2022). In STS approach, this represents the increasing tendency of technological systems to become essential parts of the organizational coordination processes and transform the operational workflows (Leavitt, 1965).

The results also revealed that the respondents perceived AI as a source of efficiency and productivity improvement. R4 explained that AI “allows me to focus on the more difficult things,” while also enabling work processes to become significantly faster. The respondent stated that tasks which previously took “seven or fourteen days can be reduced to thirty minutes.” Similarly, R6 explained that AI can help employees become “as valuable as possible,” while R1 stated that AI “can help us achieve tasks that we couldn’t do before”. The results indicate that Generative AI is seen as the instrument to increase human performance and allow organizations to perform tasks more effectively. It confirms previous sources, in which AI technologies are believed to enhance the performance of operations by automating routine work and aiding work processes that are knowledge-intensive (Brynjolfsson et al., 2023; Feuerriegel et al., 2024). This aligns with STS point of view as generative AI is enhancing employee capabilities rather than replacing human, existing work processes are improving with technological capabilities, resulting in employee performance and organizational effectiveness (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

Meanwhile, the respondents repeatedly pointed out that Generative AI also poses a significant corporate and workforce threat. Among the most common issues that were discussed is the reduction of workforce and job displacement. R3 explained that “you might need fewer people to manage tasks.” Similarly, R4 stated that “we might not need as many employees” because AI systems can perform analytical work significantly faster than humans. R5 also explained that “I expect it to reduce the number of employees required.” Such findings are consistent with the earlier literature that Gen AI may lead to a decrease in the demand in routine cognitive and administrative work and at the same time increase the necessity of more advanced digital and analytical capabilities (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017). In PSTC terms, this portrays how technological disruption can entail structural workforce change and change prevailing structure of organizational labor (Lyytinen & Newman, 2008).

The other significant finding was the increasing polarization of the workforce skills and chances. Respondents justified that the adoption of AI can result in the unequal distribution of benefits towards highly skilled workers and additional pressure on low-skilled workers. disproportionately benefit highly skilled employees while increasing pressure on lower-skilled workers. R4 described this process as “polarization,” explaining that high-skilled employees may experience “less stress and more motivation" because AI allows them to perform work "better, with better quality and faster." However, the respondent also stated that lower-level jobs "may no longer require the same level of knowledge or expertise as before." Similarly, R5 explained that "Opportunities and risks are both there, but not spread evenly between employees. Some may benefit a lot, others may have to leave." Such results indicate the possibility of Generative AI contributing to a disparity in workforce results by skills of employees and the nature of their work in an organization. This confirms previous studies that AI-enabled change can deepen the inequalities in the labor market and polarize in high and low skilled workers (Acemoglu & Restrepo, 2019; Autor, 2015). This supports PSTC view, generative AI adoption creates uneven effects on workforce during the technological transition, it varies on employees according to their ability to adapt to new technologies and evolving skill requirements (Lyytinen & Newman, 2008).

Several respondents also touched upon how the implementation of AI can make the organization more demanding and work pressure more strong. R5 explained that "management expectations [will] rise regarding how quickly everything gets done." The respondent further stated that "stress levels [will] rise due to higher expectations." This points out that whereas AI systems enhance efficiencies, it can indirectly put pressure on performance and higher productivity expectations in companies. It is in line with earlier research indicating that AI-driven workplaces can potentially augment cognitive load and pressure in terms of speed, responsiveness, and sustained productivity (Bankins et al., 2024; Szeszák et al., 2025). Companies are adjusting to capabilities of employees to adapt the technological advancement by creating new organizational pressures which supports PSTC perspective (Lyytinen & Newman, 2008).

Other issues that were identified included the concerns of trust, transparency, and reliability of AI systems. Some respondents reiterated that AI outputs must be critically verified and monitored by humans. R6 stated that "AI is more like a black box," explaining that "you can't always see where it is fundamentally wrong." Similarly, R1 stated that "you still have to check if it is really okay." R6 additionally warned that "If you do something too fast without validating the work of AI, you might be in trouble." These results show that workforces are still wary of relying on AI generated outputs too much and still see human control as a necessary part of AI assistance. This is consistent with the earlier literature on the issues related to explainability, transparency, accountability, and trust in artificial intelligence systems employed in an organization (Ferrer et al., 2021; Khogali & Mekid, 2023). From STS view, implementation of generative AI is also based on human oversight, trust, and accountability rather than only on technological capabilities, keeping organizational decision making processes to employees (Bostrom & Heinen, 1977; Mumford, 2006).

Another risk identified through the adoption of AI is data security and data governance. Respondent R4 explained that “the slowest adoption will come because of security concerns,” particularly because organizations must ensure that AI systems “will not leak information outside.” Similarly, respondent R2 highlighted concerns related to “privacy policy,” explaining that regulations and jurisdictional limitations may restrict access to operational information. These results confirm earlier studies that claim that the adoption of AI raises a significant issue on the issue of data privacy, authority and the power of organizations to access sensitive information (Taddeo et al., 2019; Zuboff, 2019). In terms of STS, these issues reflect how technical capability is not the only determinant in influencing how technologies are implemented and that institutional rules, governance systems, and organizational structures play an important part (Morton, 1991).

Another significant finding involved the role of humans in the future in Gen AI enabled logistics. Though the respondents noted the growing automation, most have highlighted that human employees would remain significant, especially in operations and physical logistics tasks. R6 explained that “logistics still involves physical work,” while also noting that many logistics tasks still require manual handling and operational judgment. Similarly, R5 stated that “People are still required,” although future work would become “less operational and more strategic”. These results indicate its perception as a modifier and not a total replicant of human activity in logistics organizations by the respondents. This confirms prior research that AI adoption tends to redistribute human and intelligent system tasks but not eradicate the role of humans

(Brynjolfsson et al., 2023; Jarrahi, 2018). From STS perspective, these findings validate generative AI as supporting tool to improve human work rather than replacing them, giving importance to human expertise, judgment, and operational involvement with organizational systems (Bostrom & Heinen, 1977; Trist & Bamforth, 1951).

In summary, the results indicate that the perception of Generative AI is both risk and an opportunity in logistics companies. Respondents linked AI adoption to operational efficiency, increased access to information, gain of productivity and innovation in the future of the organization. Yet, they raised the issues of workforce downsizing, skills polarization, organizational pressure, transparency, and problems pertaining to the governance of data as well. Both socio-technical systems theory and punctuated socio-technical change theory are supported because these findings indicate that the adoption of AI also establishes technological opportunities and socio-technical tensions that alter the system of organization, workforce configurations, and employee experiences over time (Lyytinen & Newman, 2008; Trist & Bamforth, 1951).

4.5 Generative AI and Organizational Adaptation

The findings of this study also revealed the fact that the logistics and supply chain organizations are at the initial phase of switching to the Gen AI technologies. In all the interviews, respondents reported that AI adoption is a continuous learning experience that is viewed through experimentalism, step-by-step implementation, and minimal organizational change. Employees reported that AI is being put into daily use in the operations of a company especially in communication, information retrieval and even the administration of the company, yet most organizations have yet to see significant structural or workforce changes. These results are in line with the existing research indicating that organizations tend to implement AI in small steps and build organizational readiness to wider digital transformation gradually in terms of maturity in technology and organizational processes (Budhwar et al., 2023; Dwivedi et al., 2023). In the paradigm of PSTC, these results are indicative of an initial transition period during which organizations are still in a process of adjusting to the disruptive technological systems but still the organizations are largely unchanged in terms of their structure (Lyytinen & Newman, 2008).

A key takeaway of the interviews was that Generative AI is already being utilized in everyday work practices, which is manifested through both surface level and practical usage level. Several respondents described how Gen AI tools are normally utilized to aid administration, communication, document-preparation, and information search. R3 stated that “personally I use it for day-to-day management tasks, like replying to emails or if I’m making some document.” Similarly, R6 explained that “Yeah, I use AI every day. Mainly I use Copilot.” R1 also explained that “I’m using it, but you could say that I’m still very much on the surface.” These results suggest that Generative AI has already become integrated into everyday work processes, but it is not yet used in much more complex and functional areas. This confirms prior literature that the initial use of AI in an organization is usually in low risk administration and communication, and not in broader operational integration (Davenport & Mittal, 2023; Ooi et al., 2025). According to PSTC, logistics and supply chain organization are at their early stage of generative AI adoption and they have began to adopt it in their daily work routine before becoming completing dependent on generative AI in their operations (Lyytinen & Newman, 2008).

The results also showed that a majority of organizations are yet to experience adoption of AI and organizational adjustment. Several respondents noted that integration of AI is yet to start, and that companies are just starting to realize the potential of using AI technologies. R1 explained that “We are still very much in the development phase and just starting to really use it.” Similarly, R6 stated that “I think the journey has just started.” The respondent further explained that organizations are “trying to understand how we can most efficiently use generative AI”. These results imply that companies are in a more experimental stage of adaptation, in which AI technologies are being experimented with and being slowly adapted and implemented into the ongoing workflows instead of shifting the entire organizational models at once (Davenport & Mittal, 2023; Dwivedi et al., 2023; Ooi et al., 2025). While in the PSTC context, this is a phase of initial socio-technical disruption that sees organizations start to respond to technological change, as wide-scale structural change has not taken root yet (Lyytinen and Newman, 2008).

Another significant finding was related to the growing organizational focus on the learning of AI tools and the creation of AI related skills. Some respondents described that employees should know how to deal with AI systems effectively and know how to use them in organizational contexts. R2 stated that “you should be trained to use those specific AI tools.” The respondent further explained that employees “have to spend some time getting trained.” Similarly, R1 explained that “I have been trying to learn how to use it in a correct way,” while also mentioning participation in “courses to improve my knowledge.” R6 also stated that “I have done a few courses in these tools to see what they are capable of doing.” These results suggest that the process of getting used to AI in an organization is associated with ongoing learning, whereby employees acquire some technological associations and AI-associated operational skills with time. This aligns with the prior studies that claim that the adoption of AI enhances the relevance of digital literacy, AI literacy and organizational reskilling programs in contemporary workplaces (Brynjolfsson et al., 2023; Wach et al., 2023). In terms of STS, this shows how technological change necessitates change concurrently in both the technical mechanisms and human capability (Trist & Bamforth, 1951).

The results also established that the respondents tended to view the current organizational and workload changes as comparatively small irrespective of the growth in the use of AI. A few participants described that they do not have any fundamental responsibilities, management frameworks, and workloads, which have changed significantly at the present phase of AI implementation. R5 stated that “My main responsibilities haven’t changed.” Likewise, R4 clarified that “there are no changes in responsibilities and the workload is equal.” R6 further clarified that we do things almost the same way we did before. These conclusions imply that despite the use of AI tools being more common in everyday operations, the organizations are yet to undergo any significant operational redesign or workforce redesign. This is consistent with past research that suggests that the organizational response process to Gen AI can be progressive and slow, as opposed to disruptive in nature, especially at early stages of adoption (Dwivedi et al., 2023; Hinings et al., 2018). These findings also suggest that generative AI adoption is transformed slowly because organizations adopt new technologies without changing work and organizational structures and this also aligns with the perspective of PSTC (Lyytinen & Newman, 2008).

Simultaneously, respondents explained that organizations are becoming more conscious of the fact that future integration of Gen AI into their systems may need more formal organizational control and more open governance practices. R6 explained that "We need to gain knowledge and become more mature in how to adopt AI." The respondent further stated that "AI implementation should come from the top, but also be shown in a hands-on way." Similarly, R5 explained that managerial responsibilities increasingly involve ensuring that employees "use their AI tools safely and efficiently." These results demonstrate that organizations are slowly becoming aware of the necessity of governance frameworks, implementation policies, and organizational adaptation processes to aid in the integration of Gen AI. It is consistent with previous research that highlights that the effective use of AI requires a combination of technological deployment, leadership, governance, and organizational preparedness (Bhargava et al., 2021; Senadjki et al., 2023). According to PSTC organizations are moving towards development of organizational, leadership, and governance structure which are necessary for generative AI integration (Lyytinen & Newman, 2008).

Another significant finding was the significance of organizational context and the established work processes in influencing the adaptation of AI. The respondents revealed that organizational routines, prevailing digital systems, the habits of employees, and operational structures play a critical role in AI integration. R6 stated that "It depends a lot on how people work, what they are used to, what tools they have." The respondent further explained that "some companies still rely on Excel sheets." Similarly, R4 explained that effective AI use still depends heavily on understanding "the business context." The outcomes of this indicate that the introduction of Gen AI is not standardized but instead varies according to the maturity of the organizations, technological infrastructure, the complexity involved in the tasks of the organization and the experience of the employees. These results are consistent with previous literature which suggests that generative AI adoption is dependent upon organizational structure, technology, capabilities of employees, and also the environment in which technological implementation takes place (Bhargava et al., 2021; Budhwar et al., 2023; Senadjki et al., 2023). In terms of STS, this shows that technology adoption is a result of organizational structures, work practices, employee behavior, and technological systems interacting rather than through technology alone (Leavitt, 1965; Mumford, 2006).

Psychological and cultural aspects that affected the adaptation of organisations were also discovered through the findings. R6 explained that "there is also a psychological aspect," describing how some employees resist technological change because they believe existing work methods already function effectively. The respondent explained that some employees think: "I've been doing this for 20 years, why should I change?" These results suggest that adapting AI in an organization is a process that is not just technical but also cultural, and it changes employee attitude towards the technology. It is consistent with the past studies, which propose that the tendency to resist technological change is associated with the presence of routines and identity-related issues as well as with the feeling of not being sure of what the future of work will be (Budhwar et al., 2023; Leonardi, 2011). According to STS view, it is observed that generative AI or technological adoption are dependent upon culture of organization, acceptance and willingness of employees in their operational tasks (Leavitt, 1965; Mumford, 2006).

Another interesting conclusion was that the current application of AI was perceived as being comparatively simplistic and functional more than transformational by respondents. R1 explained that current AI usage remains "on the surface, not very deep into it." Similarly, R4 stated that some internal AI tools "haven't been used much." These results suggest that, despite the growing awareness of AI and its applications, most logistics and supply chain organizations are yet to become heavy implementers of AI across the strategic or integrated operations. This reflects earlier literature suggesting that majority of organizations are at earlier stages of AI maturity when they test and apply AI to limited segments, and eventually, transform their organizations

(Davenport & Mittal, 2023; Dwivedi et al., 2023). According to the view of PSTC, organizations remain at the stage where limited implementation and experiments are taken before going deeper integration and socio technical change, which also aligns with our findings (Lyytinen & Newman, 2008).

Overall, the findings of this research indicate that the organizational adaptation to Gen AI within logistics and supply chain companies is defined at the current stage by a slow experimentation process, daily work, human resources management, and the absence of structural changes. Organizations seem to be evolving awareness, skills, and governance practices and they continue to work mostly within current organizational structures and workflows. These results can be attributed to the socio-technical systems theory and punctuated socio-technical change theory in the sense that organizations are slowly adopting generative AI in their operations and gradually changing their organizational structure rather than a sudden transformation in organizational operations, processes, and structure, that is supporting our conceptual framework which indicates that interaction of technological systems and employees transforms the organizational structure, processes, and operations with the help of employee experiences, perceptions, and daily routine tasks (Lyytinen & Newman, 2008; Trist & Bamforth, 1951).

Figure 2. Codes Cloud

5 Discussion

This chapter presents the findings of the study in relation to research questions, theoretical framework, and literature. This discussion both derives meaning of the empirical results by applying the Socio-Technical Systems (STS) theory and Punctuated Socio-Technical Change (PSTC), and also relates the results to the existing literature on the topic of artificial intelligence adoption, organizational change, and workforce dynamics in the logistics field. It also includes the practical implications of the research, constraints of the research and future research directions.

The results of the study show that generative AI is starting to play a more significant role on work processes, organizational practices, and workforce experiences in logistics and supply chain sectors. The results also indicate that generative AI technologies are mainly viewed as instruments that help to improve the efficiency of operations, automate repetitive processes, and enhance information processing. However, it is also concluded that AI implementation brings issues related to the adjustment of employees, their skill changes, job insecurity, and the necessity to monitor the process by humans.

The results showed that overall, the participants were encouraged to consider generative AI more as a facilitative technology instead of a total substitute of human labor. The respondents indicated that they used AI tools to assist them in repetitive administrative tasks, work faster, and to assist with the decision-making process. The result is consistent with the existing research indicating that generative AI assist in improving operational efficiencies and knowledge support in organizations (Brynjolfsson et al., 2023; Davenport & Mittal, 2023; Dwivedi et al., 2023). It has also been noted in previous research that AI technologies may become increasingly beneficial to businesses regarding their productivity, automatic pursuit of information routine activities, and provide even more advantages to employees (Grewal et al., 2025; Ooi et al., 2025). However, the results also show that the attitudes of employees towards AI are complex and even inconsistent. Despite the participants accepting that AI was important to improve performance and decrease human responsibilities, they were also worried about reliance on technology and their employment in the future and the anxiety of having to align with the evolving digital conditions.

This means that Gen AI changes to workforce in the future present both future opportunities and socio-psychological uncertainty to the workforce. According to STS, generative AI influences employees, task, and organizational practices apart from influencing only work processes.

The results also show that transformation in the workforce related to the implementation of Gen AI is not merely technological but occurs in a socio-technical form. Employees described that Gen AI implementation has an impact on communication styles, work tasks, organizational forms, and employee and digital system collaboration. This is a very strong observation, and it is much aligned with the assumptions of STS theory, which emphasizes the interdependence of the technological systems and the social structures within organizations (Bostrom & Heinen, 1977; Trist & Bamforth, 1951). The research demonstrates that the technological competence is not the sole factor that governs successful Gen AI integration but rather the adaptation rate among employees, organizational culture, leadership support, and human centered implementation practices.

Moreover, the findings suggest that human supervision is necessary regardless of capabilities of generative AI systems. AI generated results can be at risk of incorrectness, bias and lack of context and thus they should be verified, interpreted and monitored. In short, Gen AI systems works best when used with human knowledge and judgment (Budhwar et al., 2023; Jarrahi, 2018). The findings support the argument that the adoption of Gen AI results in hybrid work arrangements that feature employees and smart technologies working together. In the sense of STS, this is the principle of joint optimization where organizational effectiveness is a matter of balancing technological capabilities and human control, interpretation, and organizational responsibility.

Organizational learning and skill change is yet another important finding. It is observed that digital literacy, AI related skills, flexibility, and continuous learning are becoming more prominent in the workplace. This is consistent with the literature, which indicates that the application of AI is rearranging the skill profiles and imposing the pressure to reskill and upskill the labor force. According to respondents, workforce’s knowledge about technology and their capacity to collaborate with AI systems could grow in the future (Acemoglu & Restrepo, 2019; Autor, 2015; Awad & Martín-Rojas, 2024). The results consequently confirm that workforce transformation along with generative AI involves not only task automation but also broader changes in employee competencies and organizational learning methods. Simultaneously, the outcomes indicate that some employees might have a higher adaptation capacity than others based on digital skills, organizational support, and readiness to embrace technological change. In turn, AI based change can lead to the emergence of inequality in the process of adaptation in organizations, where some workers can have upskilling opportunities, and others can feel uncertain about the changes and face additional pressure to adapt to them.

The findings also revealed the issues of workforce insecurity and inconsistent organizational outcomes. According to the findings, Gen AI technologies could decrease the workforce in future, put additional performance pressure on employees, or create divisions between workers with high digital skills and those who could not adapt to technological change fast, resulting in polarization and labor uncertainty (Acemoglu et al., 2022; Bhargava et al., 2021). But the results also indicate that, at present, employees believe that generative AI is not as much a threat of job loss as it might be a resource to enhance working processes, especially because most operations in the logistics and supply chain sector cannot be completed without human coordination and interpersonal communication.

The results also indicate that the organizations are currently experiencing an early stage of GenAI transformation. This adoption is a process of slow adoption, experimentation, and a learning process, and according to PSTC view, technological innovation is disruptive and is followed by organizational adaptability and socio-technical adjustment (Lyytinen & Newman, 2008). The results suggest that the adoption of generative AI into the structure, workflows, and workforce practices of logistics and supply chain organizations is still in the process of being adopted, implying that change is not complete and is constantly developing instead of being fully stabilized.

Additionally, the results are relevant to current literature as they offer empirical support about the experiences of employees working in the logistics industry, in a sector in which studies on the adoption of generative AI are limited. Most of the previous studies had concentrated more on the technological potential of AI or macro-levels but this study offers qualitative data on how the staff perceive and experience organizational AI transformation in their daily work environments. The findings therefore contribute to expanding understanding of the human and organizational dimensions of generative AI adoption.

Overall, the discussion shows that the implementation of generative AI in logistics and supply chain companies is a complex socio-technological transformation process, which at the same time influences the work practices, the role of employees, organizational structure, and their skills. Although AI technologies offer significant efficiency, work support and innovation opportunities, the results also suggest tensions in the areas of workforce uncertainty, adaptation to new technologies in organizations, dependence on technology, and unequal employee willingness to digitally transform. The research therefore recommends that effective AI implementation is not just a matter of technological competence but also the learning within an organization, good governance, involvement of employees and capacity of organizations to strike a balance between technological development and people-oriented work practice.

5.1 Practical Implications

The results of this research lead to a number of practical implications that could be applied by organizations, managers, employees, and policymakers in the process of implementing Gen AI technologies in logistics and supply chain fields. To begin with, the results of the study indicate that companies need to implement a human centred approach in AI implementation. As employees viewed AI as the assistant technology, rather than replacement of people, companies are advised to focus on the collaboration of AI tools with employees, but not as purely automation-based solutions to the problems. To minimize the resistance and uncertainty related to change in technology, organizations must develop AI adoption procedures that enable employee participation, transparency and trust among employees so that they can see the benefits of technological change and engage in it.

Second, the findings suggest that continuous learning about AI and its implementation are vital to employee training and success. Participants raised the importance of digital skills, AI literacy, and flexibility in the workplace, which is becoming more valuable. Organizations should thus invest in reskilling and upskilling programs that would allow employees to cope better with Gen AI systems and accommodate the dynamic work demands. These initiatives could be AI training programs, workshops, online learning opportunities, and ongoing professional development.

Third, the study indicates that firms should have high levels of human supervision and governance systems when implementing Gen AI technologies. One of the issues employees raised was related to accuracy, reliability, and ethical risks of an AI generated output. As a result, companies must develop explicit policies toward the use of Gen AI, quality control, data management and ethical standards. Human validation continues to play a crucial role especially within an operating environment where inaccuracy of information can have an impact on customer service, logistical integrations, and organizational decisions.

Fourth, the results suggest that organizational leaders are also important agents that can promote socio-technical adaptation in the context of Gen AI transformation. To alleviate anxiety and uncertainty among the employees, managers should talk honestly about the aims, constraints and projected results of implementing Gen AI. Leadership must also promote organizational learning cultures that promote experimentation, flexibility, and teamwork to solve problems in the process of technological transitions.

Lastly, the results have relevant implications for the policy makers and institutions. With the growing requirements of Gen AI technologies on the labor market, educational systems and professional training institutions might have to consider the inclusion of digital literacy, AI skills, and interdisciplinary technological skills in their professional education courses. The policy makers might also be forced to take into account the policies of the labor market, which aids in supporting workforce adaptation, employee protection, and equitable access to technological learning opportunities. In summary, the implications of this dissertation emphasize that effective GenAI implementation needs a balance between technological advancement with human development, governance practices and organizational learning.

5.2 Limitations and Future Research

In this section, the limitations of this study are discussed in detail. First, the study was done through a qualitative research design with a relatively limited amount of participants, from logistics and supply chain organizations. Although qualitative study provides rich and detailed insights into employee perceptions and experiences, the findings cannot be generalized to all industries, organizations, or geographical contexts. The perceptions found in the current study indicate the experiences of individual respondents who are working in specific organizational setups.

Second, the study did not aim to measure the actual organizational performance or metrics of productivity but rather placed the emphasis on the employee and managerial perceptions toward the adoption of generative AI. Consequently, the research focuses more on the subjective experiences and interpretations rather than on the quantitative evaluation of the AI performance. Third, AI technologies that are generative are still rapidly advancing, which implies that the ways the organizations operate, and employees experience, will transform heavily in the future. The results are thus a particular step in the continuing process of Gen AI implementation and transformation of workforce. Further studies can also offer more insights into the development of the perception of employees, the adjustment of the organization, and workforce systems when AI technologies become more professional and well-developed.

Fourth, the paper largely covered organizational and workforce aspects of Gen AI adoption, without widely discussing broader ethical, legal, or societal results related to generative AI technologies. Therefore, future studies would have opportunity to explore topics based on digital privacy, employee surveillance, inequalities in jobs, and ethical governance schemes based on GenAI. Research methods such as quantitative and mixed method could also be used for future studies in order to study larger populations. Moreover, future research can examine the impacts of leadership styles, organizational culture, and national policy environments on effective socio-technical adaptation to the process of AI transformation.

Conclusively, the study suggests a significant empirical contribution to the potential relationship amid its limitations, with the adoption of generative AI and workforce transformation in logistics and supply chain organizations.

6 Conclusion

This paper discussed how generative artificial intelligence can impact workers to transform the organizational workforce in the logistics industry through perceptions and experiences of workers in relation to the use of Gen AI in the work environment. Guided by the Punctuated Socio-Technical Change (PSTC) and the Socio-Technical Systems (STS) theory, the research questions focused on how generative AI technologies affect the work practices, the organizational processes, the workforce roles, and the skills needed in the field of logistics and supply chain.

The findings reveal that the use of generative AI in logistics and supply chain is becoming more widespread as a supportive technology, enhancing efficiency and accelerating information processing, as well as helping workers with repetitive and knowledge-intensive tasks. The respondents broadly created a vision of Gen AI as an enhanced technology instead of an actual substitution of human labor. Nonetheless, the results also demonstrated that the issue of workforce adaptation, changing skills demands, employee confusion, dependence on technology, and the necessity to have human control over AI-advanced working conditions still pose a significant challenge. The study also indicated that the transformation in the workforce due to generative AI can be seen as inherently a socio-technical phenomenon. The use of Gen AI not only influences the technological processes but also changes employee responsibilities, their collaboration and learning patterns, and organizational communication. These results validate the applicability of STS theory in determining how an organization can be effective based on the interaction between the technology systems and the human centered organizational structures.

The results also confirm the PSTC viewpoint that the logistics and supply chain organizations are already passing through a continuous transition period involved with trial, error, and slight organizational restructuring with regard to Gen AI adoption. Instead of being an immediate technological surprise, the adoption of generative AI seems to be a gradual process of socio-technical adaptation where organizations struggle to accurately standardize between innovation, operational effectiveness, and adaptation of workforce. This study also contributes to the existing literature by offering qualitative empirical evidence on employee perceptions of adoption of generative AI in the logistics and supply chain sector, an area, which has been relatively underexplored so far. The authors emphasize that effective Gen AI adoption requires technological capacity, organizational learning, leadership support, employee engagement, responsible governance, and ongoing workforce development.

In general, it can be concluded that there is a great potential of the generative AI not only to change the nature of the work processes and labor organization in the logistics organizations, but also the structure of the workforce. Meanwhile, the results indicate that to have sustainable and efficient use of AI, it is necessary to balance the technological progress with the consideration of humans and organizational culture, management strategies, and wellbeing of workforces. With the ongoing development of generative AI technologies, organizations will be forced to grow, requiring the need to design adaptive socio-technology systems that facilitate the organization’s performance in addition to the responsible workforce change. The study thus leads to larger debates relating to digital transformation, socio-technical change and the future of work in the age of artificial intelligence as well as offers a realistic view on the organizational and human consequences of AI implementation in a logistics and supply chain setting.

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Appendices

Appendix 1 Questionnaire

Demographics:

- Age: 20-30, 31-39, 40-49, 50-59, 60+
- Gender: Male, Female, prefer not to answer
- Occupation: Government employee, Private employee, Business owner, Unemployed, Other (please specify)
- Education: Vocational, Bachelor's, Ph.D. Other (please specify)
- How long have you worked in the organization and what is your role in organization?

Interview Questions

1. Do you use any Generative AI systems or tools in your workplace and how do you feel about its usage at work?
2. What do you think about changes in activities after introduction of Generative AI and how were these activities handled before the introduction of Generative AI?
3. After the adoption of AI, did you need any new skills or knowledge? Have your responsibilities changed?
4. After the adoption of AI, have you noticed any changes in decision-making, management practices, or communication?
5. Can you recall a moment where AI adoption has changed how work was performed?
6. Have you experienced any challenges or resistance in adoption of AI? And how did you or your organization respond to these challenges or resistance (if any)?
7. What is your opinion on changes caused by AI on your job and workload?
8. Do you think that after the adoption of AI, stress, motivation, or income expectations are changed?
9. What do you think whether introduction of Generative AI creates more opportunities or risks for you or employees in your sector?

10. What do you think about influence of Generative AI on future of workforce, skills and job in logistics sector?

Appendix 2: Codebook

Name	Description	Sources	References
AI-Driven Transformation of Work Processes	changes in work activities and workflows resulting from the use of Gen AI	7	86
AI for documentation		6	7
Automation of tasks		2	6
Data structuring		1	1
Efficiency gains		7	22
Improved work structure		7	16
Process optimization		3	4
Reduction of manual task		5	14
route optimization		2	4
Tasks completed faster		7	13
Employee Perceptions about AI	Attitudes and opinions of employees toward the use of GenAI	7	37
AI seen as helpful		4	5
Excitement about AI		3	3
Minor resistance		4	7
no resistance		2	2
Personality-based adoption		4	9
Positive attitude		6	11
Human–AI Collaboration and Decision Support	The ways employees interact with GenAI and use it in decision-making and work activities	7	59
AI as support tool		7	20
AI not always correct		3	3
Better information availability		4	6
Human control remains important		6	18
Need to verify AI outputs		4	4
Technical usage		5	7
Opportunities vs risk	Potential benefits and risks associated with GenAI adoption	7	76
AI will grow significantly		6	16
Easier access to information		2	3

Name	Description	Sources	References
Human role still important		5	13
impact on income		4	4
Possible workforce reduction		7	15
risk		6	20
Skill requirements		4	5
Organizational Adaptation to Generative AI	How organizations and employees adjust to the introduction and use of GenAI	7	64
AI awareness		4	7
Daily AI Usage		4	4
Early-stage adoption		4	11
Learning AI tools		5	9
Limited organizational change		4	11
No major change in workload		3	4
No major skill change		5	8
Surface level usage		3	4
Training and courses		4	6