Benchmarking Operations and Supply Chain Management Practices using Generative AI: Towards a Theoretical Framework

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Abstract

Generative Artificial Intelligence (Gen AI) is an up-and-coming technological innovation that has the potential to revolutionise businesses and create significant value. Despite garnering excitement from some quarters, there are still people who are sceptical about its benefits and even fearful of its impact, particularly in the supply chain context, where it is not yet fully understood. To help academics and practitioners better understand the practical implications of Gen AI in benchmarking supply chain management practices, we propose a theoretical toolbox. This toolbox draws from ten popular organisational theories and provides a comprehensive framework for evaluating the usefulness of Gen AI. By expanding theoretical boundaries, the toolbox provides a deeper understanding of the practical applications of Gen AI for researchers and practitioners in supply chain management.

Keywords: *Generative Artificial Intelligence (Gen AI), Artificial Intelligence Supply Chain Management, Benchmarking, Organisational Theories*

1. Introduction

Benchmarking is a valuable tool for comparing an organisation's performance with others in and across various industries (Zairi, 1992; Ketter et al., 2016; Menhat et al., 2023). It is essential in operations management as it helps evaluate the benefits and drawbacks of implementing best practices to enhance efficiency, quality, and customer satisfaction (Soni & Kodali, 2010; Yusuf et al., 2014; Garcia-Buendia et al., 2024). By analysing the cash-to-cash conversion cycle (C2C), days of sales outstanding (DSO), days of payable outstanding (DPO), inventory turnover ratio, profitability, and liquidity, can gain valuable insights into optimising their supply chain and operations management processes (Gunasekaran & Kobu, 2007). The data obtained through benchmarking can be used to monitor the organisation's performance and evaluate the deviation from standard metrics, allowing the organisation to make corrective actions (Anand & Kodali, 2008; Adebanjo et al., 2010; Kamble & Gunasekaran, 2020; Choi, 2021b). This helps organisations to stay competitive and achieve their goals.

In the current business landscape, implementing innovative technology has become a game-changer for many organisations (Choi et al., 2018; Choi et al., 2020; Dhamija & Bag, 2020; Choi, 2021a; Chen et al., 2022; Choi et al., 2022; Kala & Sodhi, 2023; Ivanov, 2024a; Gupta et al., 2024). It has significantly impacted supply chain management (Xu et al., 2021; Ivanov et al., 2024b; Liu et al., 2024). This has led to a growing interest in benchmarking supply chain management practices to identify the best practices and improve business performance (Patterson et al., 2003; Peng et al., 2008; AL-Shboul et al., 2018; Ghobakhloo et al., 2024). In today's business environment, evaluating the effectiveness of supply chain management practices is crucial for businesses to remain competitive (Li et al., 2006; Choi et al., 2016; Lim et al., 2022).

When comparing a company's performance, it can be helpful to look at how it measures up to industry standards or best practices (Bagchi, 1996). Doing so can identify areas that need improvement (Asrofah et al., 2010). Benchmarking is essential because it helps organisations understand how they are doing compared to others in their industry. By doing this, organisations can identify areas for improvement and work on them. By benchmarking, organisations can gain detailed insights into their supply chain operations, identify areas that require improvement, and find ways to optimise their processes (Gunasekaran et al., 2004; Fawcett et al., 2009; Arzu et al., 2010). For example, benchmarking can help identify logistics, inventory management, or procurement inefficiencies, leading to cost savings and better customer satisfaction (Bagchi, 1996; Andersen et al., 1999). Benchmarking also helps businesses stay updated with the latest industry trends and best practices, which is crucial for remaining competitive (Guan et al., 2006). By keeping a close eye on the industry benchmarks, businesses can stay ahead of the curve and adapt to changes in the market (Anand & Kodali, 2008). Overall, benchmarking is an essential tool for businesses to evaluate the effectiveness of their supply chain management practices (Bagchi, 1996; Peng Wong & Yew Wong, 2008).

As the world transitions into the Gen AI era, the benchmarking of supply chain management practices continues to evolve (Fosso Wamba et al., 2023a). It is a complex challenge that demands constant attention and adaptation. With the rise of AI-powered technologies, supply chain management practices are being transformed unprecedentedly (Helo & Hao, 2022; Mithas et al., 2022; Mithas et al., 2022; Fosso Wamba et al., 2023b; Arsenyan & Piepenbrink, 2024). Organisations must embrace technological innovations from predictive analytics to automated decision-making to remain competitive (Yan et al., 2022; Jackson & Ivanov, 2023; Wang et al., 2023; Abu Huson et al., 2024; Amaya & Holweg, 2024). As companies strive to optimise their operations and improve efficiency, benchmarking supply chain management practices will continue to be critical to success in the Gen AI era. Gen AI is an artificial intelligence technology that generates text, images, videos, and other data using generative models (Feuerriegel et al., 2024). Expanding upon the concept of Gen AI, we will delve into the significance of its capacity to produce textual content, images, videos, and various forms of data. This technological capability can be precious for supply chain managers as they make informed decisions (Fosso Wamba et al., 2023b).

The adoption of Gen AI in operations and supply chain management has been debated among scholars, policymakers, and industry professionals (Fosso Wamba et al., 2023a; Kuo & Choi, 2024). While some believe that this technology can help benchmark their practices against those in similar or different industries, others need to be more sceptical about its usefulness in sustaining a competitive advantage (Richey Jr. et al., 2023). Those who are hesitant about using Gen AI express concerns about the accuracy and reliability of the data generated by the technology (Ooi et al., 2023). They worry that the data may need to be more comprehensive to provide a clear picture of the industry's best practices. Additionally, they question whether the technology can factor in the nuances of individual organisations and their unique supply chain challenges (Fosso Wamba et al., 2023b). Despite these concerns, some industry professionals have successfully utilised Gen AI to benchmark their practices and gain a competitive edge (Kanbach et al., 2024; Jackson et al., 2024). By analysing data from multiple sources, including competitors and other industries, they have identified areas to improve their operations and supply chain management (Kumar et al., 2018).

Gen AI has attracted attention from several companies, including notable names such as General Mills (Norton, 2024), Toyota (Toyota Newsroom, 2023), Volkswagen (CDO Magazine Bureau, 2024), AWS, and numerous SMEs (Shore et al., 2024). These organisations use Gen AI for various vital functions like demand forecasting, materials planning, transportation planning, and real-time tracking of supply chain metrics. The reliance on Gen AI highlights the increasing importance of advanced technologies in optimising business operations and decision-making processes. According to Norton (2024), General Mills utilises a large language model (LLM) to engage with customers, allowing the company to understand customer needs and accurately forecast demand, which informs their planning processes. Additionally, top automotive companies Toyota and Volkswagen have invested substantially in their AI labs, utilising them for research and development and customer service applications. These companies are leveraging Gen AI features to enhance communication with customers, dealers, and service stations, showcasing their innovative approach to AI technologies. Amazon Web Services (AWS) has revolutionised customer engagement using Gen AI to empower businesses to anticipate and plan for market fluctuations.

Despite significant innovation, the adoption of Gen AI in operations and supply chain management is still in its early stages (Bendoly et al., 2023). While it has the potential to provide valuable insights, it is essential to consider its limitations and evaluate its effectiveness on a case-by-case basis (Kar et al., 2023). Gen AI represents a significant shift from previous technological innovations in three possible ways: *adaptability, affordability and accessibility*. Firstly, Gen AI is highly adaptable, which means it can learn and evolve to suit different circumstances and tasks. This *adaptability* is due to the algorithms and machine learning models that power Gen AI, allowing it to improve and refine its responses based on new information continually. In addition to its adaptability, Gen AI is also highly *affordable* compared to previous technologies. This is because many underlying technologies that power Gen AI, such as cloud computing and open-source software, have become more accessible and cost-effective in recent years. This has made it easier for businesses and individuals to leverage Gen AI for various applications, from customer service to healthcare. Finally, Gen AI is also highly *accessible*, meaning anyone with an internet connection or a smartphone can use it. This accessibility is due to the proliferation of mobile devices and the internet, which have made it easier for people to access and use Gen AI-powered services and applications. As a result, Gen AI has the potential to reach a much broader audience than previous technologies, which were often limited to specific industries or use cases.

Gen AI is a revolutionary technology that can transform how we live, work, and interact with each other (Dwivedi et al., 2023; Akhtar et al., 2024). It uses algorithms to create new data that mimics the patterns and behaviours of existing data (Shore et al., 2024). This makes it an extremely adaptable technology used in various fields. Additionally, it is affordable and easily accessible, which sets it apart from other technological innovations that are often expensive and difficult to access. Gen AI represents a significant departure from past technological advancements, which relied on solid theoretical arguments to support their development. Although theoretical arguments are still vital, the adaptability and accessibility of Gen AI mean that it can be used in practical applications without requiring the same level of theoretical support.

Due to its versatility, Gen AI has the potential to be an invaluable tool for scholars, managers, and policymakers who are interested in operations and supply chain management benchmarking. It can generate data to help these individuals make informed decisions that will benefit their organisations and those they serve. Overall, Gen AI is a powerful technology that has the potential to bring about profound changes in the world. Therefore, this study aims to provide scholars with a portfolio of key and emerging theories to help them understand the evolution of Gen AI and use it effectively in benchmarking operations and supply chain management practices. We will explore each theory in detail to provide a comprehensive understanding of its significance in the field of Gen AI. Additionally, we will analyse the potential implications of these theories on organisational practices. The goal of this paper is to provide scholars and practitioners with a set of insights that can help them leverage Gen AI to enhance their organisational performance.

The paper is structured into six sections. The second section delves into the underlying theories, while the third explores the theoretical toolbox. The fourth section presents a theoretical framework that helps establish a conceptual link between the drivers or factors of Gen AI, the specific conditions, and a theoretical framework. The fifth section discusses the study's contributions to theory, managers, policymakers, and future research directions. Finally, we conclude the paper.

2. Theoretical Background

2.1 Benchmarking

Benchmarking is a management practice that involves comparing an organisation's processes, strategies, and performance against those of industry leaders or competitors (Bagchi, 1996; Anand & Kodali, 2008). The concept of benchmarking has gained significant attention over the past five decades as it has proven to be an effective tool for improving an organisation's performance, identifying areas for improvement, and promoting innovation (Willmington et al., 2022). By identifying best practices and industry standards, benchmarking allows organisations to set goals and targets that are realistic and achievable (Magd & Curry, 2003). Moreover, benchmarking provides a means for organisations to measure the success of their efforts and make data-driven decisions that can improve efficiency, productivity, and competitiveness (Kamble & Gunasekaran, 2020; Almazmomi et al., 2022).

Organisations have implemented benchmarking practices to measure and compare their performance against industry standards and competitors. As a result, they have developed various performance measurement tools, each with unique benefits. Two commonly used frameworks are the Balanced Scorecard (Kaplan & Norton, 1992) and the SCOR framework by the Supply Chain Council in 1996, now owned by The Association of Supply Chain Management (Lockamy & McCormack, 2004; Guillot et al., 2024). The Balanced Scorecard is a strategic management tool focusing on four key areas: *financial performance*, *customer satisfaction*, *internal processes*, and *learning and growth*. On the other hand, the SCOR framework is a supply chain management tool that aims to improve supply chain performance by providing a common language, metrics, and best practices for all stakeholders involved. Both frameworks have proven effective in enhancing performance and driving organisational success (Peng Wong & Yew Wong, 2008). As we move into the digital transformation era, benchmarking tools will evolve significantly. The application of Gen AI will play a crucial role in shaping the future of benchmarking tools, allowing for faster and more accurate data analysis and trends. This will undoubtedly lead to more effective decision-making and better business outcomes.

2.2 Performance Measurement Systems (PMS)

The performance measurement system plays a vital role in analysing and improving the performance of the supply chain (Beamon, 1999; Gunasekaran & Kobu, 2007; Maestrini et al., 2017). To achieve this, we have developed a performance measurement system based on the widely recognised SCOR framework (Sellitto et al., 2015; Lima-Junior & Carpinetti, 2019). The SCOR (Supply Chain Operations Reference) model was first developed under the ownership of the Supply Chain Council in collaboration with PRTM and AMR Research (Lambert & Enz, 2017). It is overseen by the Association for Supply Chain Management (ASCM). SCOR provides a comprehensive framework for evaluating and benchmarking supply chain performance across six key processes: plan, source, make, deliver, return, and enable (Guillot et al., 2024). This model offers a systematic approach for organisations to assess and enhance their supply chain operations. The SCOR framework classifies all supply chain activities into six major groups: plan, source, make, deliver, return, and enable (Cannas et al., 2024). This study will delve into each activity and present a detailed analysis of the performance metrics critical to the current scenario (see Table 1). By doing so, we aim to provide a comprehensive understanding of the supply chain performance and identify opportunities for improvement.

Table 1: SCOR-Based Performance Measurement Systems

Supply chain processes	Specific activities	Metrics
Plan	Production planning includes inventory planning, capacity planning, and distribution planning.	Lead time, throughput, takt time, production attainment, inventory in days, inventory turnover ratio, capacity utilisation, and on-time delivery (OTD).
Source	Selecting the appropriate supplier and conducting quality control checks on incoming raw materials are essential steps in ensuring the quality of our products.	Compliance rate, defects rate, purchase order cycle time, responsiveness, procurement return on investment (PROI)

Make	Manufacturing schedule, maintenance schedule	Manufacturing cycle time, time between changeovers, overall equipment efficiency (OEE)
Deliver	Stocking of finished goods in warehouse/ distribution centres, shipment cycle, last-mile delivery	Delivery lead time, customer fill rate, customer satisfaction index
Return	Supply chain network design, reverse logistics, environmental packaging	Recycling rate, recovery percentage
Enable	Compliance with regulatory norms, supply chain risk management plan, supply chain network design	Flexibility, agility, resilience

(Source: Authors own compilation)

Table 1 is a collection of information that we have put together from various reliable sources. These sources include academic literature, such as the works of Cannas et al. (2024), Rolf et al. (2023), and Guillot et al. (2024). We have also taken insights from consulting reports from E&Y (Dutta & Steinberg, 2023) and IBM (Cushman et al., 2023). This compilation provides a comprehensive understanding of the primary supply chain metrics that can be affected by AI-based companion tools or Gen AI. We will discuss these in detail in the following sections.

2.3 Gen AI

Gen AI, creative AI or synthetic AI is a form of artificial intelligence that can generate complex data, such as images, music, or text, without human intervention (Dwivedi et al., 2023; Grimes et al., 2023; Susarla et al., 2023; Alsharhan et al., 2024). It is the third generation of AI technology, following rule-based AI and statistical AI (Banh & Strobel, 2023; Yu et al., 2024). Gen AI is based on a machine learning algorithm known as generative adversarial networks (GANs), which pits two neural networks against each other to create new, unique outputs (Dash et al., 2022). This technology can potentially revolutionise several industries, including art, design, and advertising, by enabling the creation of new and original content that was previously impossible for humans to produce.

It can create complex models and generate data that can assist humans in making quick and informed decisions (Banh & Strobel, 2023). This technology has been developed by combining the power of deep learning, machine learning, and neural networks, which enables it to analyse and interpret vast amounts of data with remarkable accuracy. Gen AI can understand and respond to complex human queries, unlike previous-generation AI or technologies. It is a powerful tool in various industries, including healthcare, education, finance, and entertainment (Saetra, 2023). With its ability to learn and adapt to new situations, Gen AI is poised to be at the forefront of the AI industry, making it an exciting time for developers and end-users. Therefore, our strong contention is that the upcoming Gen AI will provide a precious platform for developing benchmarking tools. These tools will enable us to perform benchmarking with multiple industries, creating effective strategies for long-term success.

2.4 Toolbox

The concept of a "*toolbox*" is frequently used by scholars in organisational studies to illustrate how an individual can adopt any theory from a range of available theories (see Craighead et al., 2020). It is like a mechanic repairing a machine with a toolbox containing various tools that can be used for different purposes. This toolbox metaphor implies that a scholar has a range of tools, such as methods, concepts, and theories, that they can employ to address various organisational issues effectively (Yanow, 2012; Avdiji et al., 2020). The toolbox concept also highlights the importance of having diverse tools available to meet different needs and challenges within the organisation. In this paper, we aim to provide a toolbox of relevant theories that can assist scholars in understanding Gen AI. By understanding the role of these theories, scholars can enhance their knowledge of how Gen AI can help organisations benchmark their practices against other industries (Mariani & Dwivedi, 2024).

2.5 Organisational Theories

Theories are increasingly important in understanding and interpreting the complex phenomena of modern businesses (Weick, 1989). These theories provide a framework for analysing how organisations operate, their structure, and the factors influencing their success (Astley & Van de Ven, 1983). By examining the different perspectives of organisational theories, researchers can gain a deeper understanding of the inner workings of organisations and how they can be improved (Ketchen & Hult, 2007; Sarkis et al., 2011; Gunasekaran et al., 2018; Zhu et al., 2022). Moreover, organisational theories have practical applications in management, leadership, and strategic planning, making them essential tools for modern businesses (de Camargo Fiorini et al., 2018). The study of operations and supply chain management has employed several theories to explain various phenomena over the years (Ketchen & Hult, 2007). Among the most popular of these theories are the resource-based view, which focuses on the role of resources in creating competitive advantages (Barney, 1991); the dynamic capability view (Teece et al., 1997), which emphasises the importance of a firm's ability to adapt and change in response to changing environments; institutional theory, which seeks to explain how societal norms and expectations shape organisational behaviour (DiMaggio & Powell, 1983); stakeholder theory, which argues that firms must take into account the needs and interests of all stakeholders (Parmar et al., 2010); contingency theory, which posits that the most effective organisational practices vary depending on the situation (Sousa & Voss, 2008); resource orchestration theory, which explores how firms can combine different resources to achieve desired outcomes (Sirmon et al., 2011); resource dependence theory, which examines the relationships between organisations and their external environment (Pfeffer & Salancik, 1977); strategic choice theory, which focuses on the decision-making processes involved in strategy formulation and implementation (Miles et al., 1978); organisational information-processing theory, which looks at how organisations acquire, process, and use information to make decisions (Galbraith, 1974); and relational view, which stresses the importance of relationships and interactions between firms in shaping their behaviour and performance (see, Dyer & Singh, 1998; Ketchen and Hult, 2007; Craighead et al., 2020).

3. Theoretical Toolbox for Gen AI

In this section, we will delve into ten theories that have the potential to aid organisational scholars in answering crucial questions that continue to perplex them, as well as practitioners seeking to gain a better understanding of Gen AI and its application in benchmarking supply chain practices. The theories we will discuss will be thoroughly examined, and their practical implications will be explored in detail. We seek to provide a comprehensive and insightful analysis of these theories, enabling our readers to acquire a more nuanced and informed perspective on the subject matter. By the end of this section, we aim to equip our readers with the knowledge and tools necessary to navigate the complex landscape of Gen AI and supply chain benchmarking effectively.

3.1 Resource Based Theory

Resource-based theory (RBT) is a widely recognised and popular theoretical lens used by scholars to understand how the resources and capabilities of an organisation can provide it with a competitive edge over its rivals (Barney, 1991). According to RBT, organisations can achieve a competitive advantage by focusing on their strategic resources and capabilities and uniquely bundling them (Brandon-Jones et al., 2014). Operations and supply chain management scholars have extensively used the theory to examine how resources and capability can be the source of competitive advantage (Hitt et al., 2016). However, despite its popularity, critics have pointed out several limitations of the theory. For example, the theory fails to explain *when* and under *what* circumstances these resources and capabilities generate a competitive edge (Aragon-Correa & Sharma, 2003). Additionally, the theory needs to explain the importance of social dimensions, as it tends to focus solely on economic criteria (Oliver, 1997). Therefore, while RBT is a valuable framework for understanding the resources and capabilities of an organisation, it is imperative to consider its limitations and supplement it with other theories to gain a more comprehensive understanding of the competitive landscape. Firms' resource-based view (RBV) focuses on an organisation's internal resources as a source of sustainable competitive advantage. However, the contingent view of the RBV (C-RBV) suggests that a firm's competitive advantage depends on its external environment and internal resources (Aragon-Correa & Sharma, 2003; Brandon-Jones et al., 2014). In this context, Gene AI can be a valuable tool for organisations to gain a competitive advantage, but only under certain circumstances (Tiwari et al., 2024a). The C-RBV framework can help understand these circumstances and identify the situations where Gen AI can be most effective in enhancing the strategic capabilities of a firm. Therefore, by applying the C-RBV framework, organisations can make informed decisions about using Gen AI and maximise its potential to create value and gain a competitive advantage.

Today's organisations that depend heavily on technology have been criticised for lacking sensitivity towards social issues and focusing solely on economic goals (Warschauer, 2004). This approach, which prioritises profits over social responsibility, has led many to question the actual value of such organisations (Oliver, 1997). However, with the advent of Gen AI, organisations have an opportunity to change the way they operate. By utilising Gen AI, organisations can gain a deeper understanding of how to use institutional theory and resource-based view as complementary theoretical lenses to view the usefulness of Gen AI in a more socially responsible manner (Dubey et al., 2019). Institutional theory helps organisations understand how they fit into the larger social and cultural contexts in which they operate. It allows organisations to understand how their actions and decisions impact society and helps them identify areas where they can improve their social responsibility (Oliver, 1997).

Conversely, the resource-based view helps organisations understand how to use their unique resources and capabilities to gain a competitive advantage. By applying a resource-based view to Gen AI, organisations can identify new opportunities to use Gen AI in a way that benefits society and the organisation (Oliver, 1997; Peng et al., 2009). Therefore, by utilising institutional theory and resource-based view, organisations can gain a more comprehensive understanding of the usefulness of Gen AI and use it more socially responsibly.

3.2 Dynamic Capability View

The dynamic capability view (DCV) is a theoretical framework that builds on the resource-based view (RBV) to help organisations develop and sustain competitive advantages in a constantly changing business environment (Teece et al., 1997; Teece, 2007). One of the critical insights of the DCV is that organisations must adapt and innovate their resources and capabilities to address the evolving demands of the market (Eisenhardt & Martin, 2000). This requires a strategic focus on building dynamic capabilities, the skills, processes, and routines that enable organisations to sense and respond to environmental changes (Teece, 2007). The DCV emphasises that dynamic capabilities are not just a one-time effort but an ongoing process of learning and improvement (Eisenhardt & Martin, 2000). Organisations must be able to scan the environment for new opportunities and threats, experiment with different approaches to address them, and then integrate successful practices into their existing routines (Fainshmidt et al., 2016). By developing dynamic capabilities, organisations can create a sustainable competitive advantage to thrive in an increasingly complex and uncertain business environment (Schilke et al., 2018).

In today's fast-paced business world, organisations constantly look for new ways to stay ahead of the competition (Munir et al., 2022; Stark et al., 2023; Bag et al., 2024; Le & Behl, 2024). One strategy that many are considering is the development of Gen AI capability. This refers to the ability of an organisation to create and use AI algorithms that can learn and evolve, enabling the organisation to respond quickly and effectively to changing market conditions. By building Gen AI capability as a dynamic capability, organisations can ensure that they are always able to adapt to new challenges and opportunities. This requires a commitment to ongoing learning and development and a willingness to invest in the necessary tools and resources. However, the potential benefits are significant, including increased efficiency, better decision-making, and a more competitive position in the marketplace. Overall, developing Gen AI capability is essential for any organisation that wants to stay relevant and competitive in today's business environment. Organisations can position themselves for long-term success and continued growth by taking a strategic approach to AI development.

3.3 Institutional Theory

Institutional theory is a sociological concept that deals with how organisations respond to external pressures to conform to societal norms and expectations (DiMaggio & Powell, 1983; Kauppi, 2013). In the context of operations and supply chain management research, institutional theory has become increasingly crucial due to the growing need for organisations to legitimise their actions in the eyes of the public, stakeholders, and regulatory bodies (Ketchen & Hult, 2007; Sarkis et al., 2011; Bag et al., 2021). This theory posits that organisations are not just economic entities, but also social ones influenced by culture, values, and norms (Peng et al., 2009). As such, organisations are often compelled to align their practices with the prevailing institutional norms of their environment to gain legitimacy and social acceptance.

In operations and supply chain management, institutional theory provides valuable insights into how organisations can navigate the complex social expectations and norms that influence their actions (Kauppi, 2013). By understanding the institutional pressures that affect their behaviour, organisations can make informed decisions that enhance their legitimacy and contribute to the broader goals of sustainability and social responsibility. In the preceding section, we explored how institutional theory can be a valuable addition to the firm's resource-based view (RBV). An institutional theory emphasises the importance of social norms and values in shaping organisational behaviour, and it can help organisations understand how to navigate complex regulatory environments and comply with ethical standards. In practice, institutional theory can inform the use of Gen AI by guiding organisations in developing systems that align with regulatory norms. For example, companies can use Gen AI to analyse large datasets and identify patterns consistent with regulatory requirements. This can help organisations avoid penalties for non-compliance and ensure they operate within the law's bounds. Moreover, institutional theory can also guide ethical considerations. By understanding the norms and values underpinning their industry, companies can use Gen AI to develop systems consistent with those norms. This can help organisations avoid reputational damage and build trust with stakeholders. Institutional theory can be a powerful tool for organisations seeking to leverage Gen AI responsibly and effectively. By using this theory to guide their approach, companies can ensure that their use of AI aligns with social norms and values and avoids potential ethical and legal pitfalls.

3.4 Contingency Theory

Contingency theory refers to the management approach that recognises the importance of adapting to specific situations rather than relying on a one-size-fits-all approach (Csaszar & Ostler, 2020). This theory has gained significant attention in operations and supply chain management, emphasising the need to adjust operations and supply chain activities based on specific circumstances, such as product type, customer demand, and market conditions (Sousa & Voss, 2008). The contingency theory is a valuable tool organisations can use to evaluate the specific conditions under which Gen AI can be implemented to deliver superior results. Numerous organisations currently use Gen AI to automate tasks, improve efficiency and reduce costs. However, it is essential to recognise that not all situations are the same, and a one-size-fits-all approach may not be practical in all cases (Volberda et al., 2012). Therefore, organisations need to understand the potential benefits and limitations of Gen AI and its suitability for their specific needs. A detailed analysis of the organisation's operations, goals, and objectives can help determine whether Gen AI is the right solution for them.

Moreover, based on previous experiences with other technological innovations, organisations must realise that implementing a new technology requires a comprehensive approach. This includes understanding the impact of the technology on the organisation's structure, processes, and culture (Butt et al., 2024). It also means recognising that proper training and support are essential to ensure the successful adoption and use of the technology. In conclusion, while Gen AI can offer significant benefits to organisations, assessing the specific conditions under which it can be used effectively is crucial. A tailored approach can help organisations achieve optimal results while recognising that a one-size-fits-all approach may not be the best solution for every situation.

3.5 Stakeholder Theory

Stakeholder theory is a useful theoretical lens that considers the opinion of stakeholders, including government, customers, suppliers, investors, shareholders, and ordinary citizens while making decisions (Freeman, 1984). These stakeholders may include employees, customers, suppliers, shareholders, government bodies, and the wider community (Jones et al., 2007). By considering the needs and expectations of these groups, organisations can make more informed and responsible decisions that align with considered objectives (Parmar et al., 2010; Sodhi, 2015). In today's business world, where social and environmental issues are becoming increasingly important, stakeholder theory has become a crucial tool for creating sustainable and ethical business practices (Reynolds et al., 2006).

Adopting technological innovations is crucial for organisations to stay competitive in today's fast-paced business environment. However, research has not paid much attention to the stakeholders' perspective. The stakeholders' views can provide valuable insight for organisations that are considering the adoption of any innovation. Stakeholders can be anyone affected by the organisation's actions, including customers, employees, shareholders, and suppliers. Their perspective can offer a helpful guide for organisations contemplating the adoption of new technologies. For instance, if an organisation is considering the adoption of Gen AI, understanding the stakeholders' opinions and views on the adoption can provide a better understanding of whether it is a good idea. The stakeholders' views can also help organisations identify potential challenges and opportunities for adopting new technologies. This can help organisations prepare better and make informed decisions that align with their goals and objectives. In conclusion, the stakeholders' perspective is a crucial aspect that should be considered when considering the adoption of any technological innovation. By considering the stakeholders' views, organisations can make better decisions and ensure that adopting new technologies is successful.

3.6 Resource Orchestration Theory (ROT)

Resource orchestration theory is a management concept that builds upon the principles of the resource-based view (Sirmon et al., 2011). It focuses on how a firm can manage its resources and capabilities effectively to achieve a competitive advantage. The theory emphasises the importance of possessing valuable and rare resources and effectively coordinating and leveraging them to create value (Liu et al., 2016). In other words, more is needed to have valuable resources; a firm must also be able to orchestrate them to maximise their potential (Hughes et al., 2018). A firm can achieve a sustainable competitive advantage over its rivals (Queiroz et al., 2022). According to Sirmon et al. (2011), resource orchestration theory proposes three key actions organisations can take to effectively manage and leverage their resources. These actions are *structuring*, *bundling*, *and leveraging*. Structuring involves organising resources to facilitate their efficient and effective use. This may include creating processes and procedures, designing roles and responsibilities, and establishing communication channels, among other things. Bundling, on the other hand, involves combining resources in a way that creates synergies and enhances their value. This may involve bundling complementary resources to create a more integrated offering or bundling resources in a way that allows for economies of scale or scope. Finally, leveraging resources involves using them strategically to create a competitive advantage. This may involve exploiting unique capabilities or assets or leveraging resources to enter new markets or pursue new opportunities (Craighead et al., 2020). Overall, these three actions represent essential strategies organisations can use to maximise the value of their resources and achieve long-term success.

The ROT is a helpful framework for organisations considering adopting Gen AI. In the first step of structuring, the organisation can identify its existing resources and capabilities and align them with the goals of adopting Gen AI. Next, the organisation can generate value by bundling these resources and capabilities to create a synergistic effect. Finally, leveraging these bundled resources allows the organisation to gain a competitive advantage and explore new opportunities. The ROT can help organisations develop effective strategies to optimise their resources when adopting Gen AI. By adopting this theory, organisations can identify the essential resources and capabilities that can be leveraged to create value and competitive advantage. This can lead to developing a comprehensive strategy to help organisations achieve their goals more efficiently and effectively.

3.7 Stimulus-Organism-Response (S-O-R) theory

The Stimulus-Organism-Response (S-O-R) theory is a valuable tool organisations can use to understand better the factors that drive the adoption of different practices and behaviours (Mehrabian & Russell, 1974). According to this theory, external stimuli can influence an organism's internal state, affecting the organism's response to those stimuli (Partington, 2000). This means that organisations can identify the specific stimuli that lead to adopting certain practices or behaviours, such as changes in organisational culture, new technologies, or shifts in market demand (Upadhyay & Kamble, 2023). By understanding these stimuli, organisations can more effectively design and implement practices that align with their goals and objectives and ultimately drive long-term success.

Hence, the S-O-R theory can be a helpful framework that can assist organisations in making informed decisions about adopting Gen AI. This theory suggests that the environment (stimulus) affects the internal processes and structures of an organism (organism), leading to a specific response (response). In the case of Gen AI, the stimuli could be the data inputs, which affect the internal processes of the AI model. The organism is the Gen AI system, which processes the data inputs to produce an output. The response is the output generated by the system. By understanding the S-O-R theory, organisations can identify the relevant stimuli and design the Gen AI system accordingly. For example, organisations can ensure that the input data is high quality, applicable to the desired output, and diverse enough to cover different scenarios.

Organisations can also design the AI model robust and efficient, with appropriate algorithms and architectures to handle the input data effectively. Overall, the S-O-R theory provides a helpful direction for organisations considering the adoption of Gen AI, helping them design and implement effective AI systems to deliver the desired outcomes.

Although the S-O-R framework is widely used in various fields, it has yet to be fully explored by scholars in operations and supply chain management. The S-O-R framework can be a valuable tool for understanding how Gen AI can be utilised to benchmark supply chain management practices. Scholars can better understand how technology can improve supply chain performance and efficiency by exploring the S-O-R framework in supply chain management. Gen AI has the potential to revolutionise the way supply chain management is conducted by enabling the creation of predictive models and simulations that can be used to optimise various aspects of the supply chain. Therefore, a deeper understanding of the S-O-R framework and Gen AI can help organisations develop effective supply chain strategies and stay ahead of the competition.

3.8 Organisational Information Processing Theory (OIPT)

Organisational Information Processing Theory (OIPT) is a theoretical framework that explains how organisations process information to gain a competitive advantage (Galbraith, 1974). According to OIPT, organisations can improve their information processing capability by adopting various strategies, such as investing in advanced information technology, enhancing communication channels, and improving decision-making processes (Bensaou & Venkatraman, 1995). By doing so, organisations can increase efficiency, reduce operational costs, and ultimately gain a competitive edge in the market (Tushman & Nadler, 1978; Mithas et al., 2011). OIPT emphasises the importance of effective and efficient information processing in organisations (Srinivasan & Swink, 2018; Sharma et al., 2024). It suggests that organisations better equipped to handle and process information are better equipped to respond to changes in the market and take advantage of emerging opportunities (Gattiker, 2007). OIPT argues that the ability to process information faster and more accurately than competitors is a significant competitive advantage in today's fast-paced business environment (Srinivasan & Swink, 2018; Dubey et al., 2021; Tiwari et al., 2024b). In summary, OIPT offers a comprehensive framework for organisations to improve their information processing capability and generate a competitive advantage. By adopting the strategies proposed by OIPT, organisations can become more efficient, effective, and agile in their decision-making processes, ultimately leading to more tremendous success in the marketplace.

Gen AI that can process massive amounts of data and generate new insights and ideas. This feature makes it an invaluable tool for organisations operating in highly uncertain environments. By utilising Gen AI, businesses can gain a competitive edge by predicting future trends, identifying new opportunities, and creating innovative solutions. Additionally, this technology can help organisations optimise their operations, reduce costs, and enhance customer satisfaction. In summary, the OIPT offers a robust theoretical framework to understand how Gen AI can benefit organisations in various ways, including benchmarking supply chain management practices.

3.9 Upper Echelon Theory (UET)

The role of top management in successfully adopting new technology cannot be overstated. Hambrick and Mason (1984) suggest that the choices made by an organisation are a direct reflection of the beliefs and priorities of its top managers. This means that the managers responsible for leading an organisation must be guided in shaping their strategies, ensuring they are grounded in their core beliefs and values (Liang et al., 2007). Moreover, top managers must work to strengthen these beliefs and ensure that the organisation remains committed to pursuing its goals (Bartlett & Ghoshal, 1994)). This requires a deep understanding of the organisation's culture and an ability to communicate effectively with employees at all levels of the organisation (Geletkanycz, 1997). By doing so, top managers can create a sense of shared purpose and help build a culture of innovation that supports the successful adoption of technology (Carpenter et al., 2004; Liang et al., 2007; Dubey et al., 2019).

In practice, this means that top managers must proactively identify opportunities for technology adoption and develop strategies tailored to their organisation's needs (Grover, 1993). They must also be willing to invest in the necessary resources and infrastructure to support successful technology adoption, such as training programs, data management systems, and IT infrastructure (Liang et al., 2007). Implementing new technology requires top management's involvement and commitment at every process stage. Therefore, we believe that the level of belief and commitment from top management plays a crucial role in adopting Gen AI. This distinguishes organisations that have successfully utilised Gen AI to benchmark their supply chain practices from those still considering their options.

Scholars of operations and supply chain management can explore six significant questions about how Gen AI can assist in benchmarking operations and supply chain management practices based on these theories. The first question that arises when considering the adoption of Gen AI by organisations is what motivates them to do so. This inquiry deals with the underlying factors or drivers influencing their decision to adopt Gen AI. These factors could include a range of variables, such as the organisation's existing resources and capabilities, the potential benefits of Gen AI for their business operations, or institutional factors that encourage or prompt them to explore this technology. For instance, an organisation may adopt Gen AI to improve its product design and development process, reduce costs, enhance customer experience, or gain a competitive edge. Institutional factors such as regulatory changes, industry standards, or market trends may influence an organisation's decision to adopt Gen AI. Therefore, understanding the "*what*" and "*why*" aspects of organisations' adoption of Gen AI requires a comprehensive analysis of these underlying factors and drivers.

3.10 Relational View (RV)

In today's fast-paced and complex business environment, organisations must build strong relationships with their stakeholders to gain a competitive edge. According to Dyer & Singh (1998), this can be achieved by fostering trust, collaboration, and information sharing. By engaging in these relational competencies, organisations can create a strong network, which can be beneficial in various ways (Moshtari, 2016). For instance, information sharing can help organisations stay updated with the latest industry trends, practices, and insights, enabling them to make more informed decisions and stay ahead of their competitors (Latunreng & Nasirin, 2019). Trust-building, on the other hand, can help organisations establish a positive reputation and credibility in the eyes of their stakeholders, leading to increased loyalty, repeat business, and referrals (Morgan & Hunt, 1994; Schulze & Krumm, 2017; Dubey et al., 2020). Collaboration is also an essential relational competency that can help organisations achieve their goals more effectively by leveraging their collective strengths, expertise, and resources (Hardy et al., 2005), leading to shared success, improved outcomes, and enhanced innovation.

Building strong relationships based on vital relational competencies can be a game-changer for organisations looking to gain a competitive edge (Dutta et al., 2020). Trust and effective collaboration are critical factors that explain the successful application of Gen AI in benchmarking supply chain practices (Fosso Wamba et al., 2023a).

The decision to adopt Gen AI involves several factors that organisations need to consider carefully. One of the key questions that organisations need to answer is "*when" to* adopt Gen AI. The contingency theory can be a valuable framework for addressing this question. This theory proposes that the effectiveness of a particular approach or strategy is contingent upon the specific circumstances in which it is implemented. In the case of Gen AI adoption, organisations need to consider various internal and external factors before deciding on the optimal time to introduce Gen AI into their operations. These factors may include their technological capabilities, market trends, and regulatory environment. By taking a contingency-based approach, organisations can make more informed decisions about when to adopt Gen AI and ensure that they are well-positioned to reap the benefits of this powerful technology.

Moreover, the contingency theory, combined with the resource-based or dynamic capability view, may provide a better understanding of "*what*" and "*when*". The resource-based view emphasises leveraging an organisation's unique resources and capabilities to gain a competitive advantage. By combining these views with the contingency theory, organisations can better understand the critical factors for successful Gen AI adoption and implementation. Therefore, the decision to adopt Gen AI is complex and requires careful consideration of various internal and external factors. By combining a contingency-based approach with the resource-based and dynamic capability views, organisations can make more informed decisions about when to adopt Gen AI and ensure that they are well-positioned to reap the benefits of this powerful technology.

External factors, such as stakeholder pressure or competition, can influence the adoption of Gen AI. For instance, if a company's competitors already leverage the benefits of Gen AI to gain a competitive advantage, it may feel pressured to follow suit. Similarly, if stakeholders, such as investors or customers, demand AI-powered tools, organisations may have to adopt Gen AI to meet their expectations. Institutional theory provides a valuable lens to understand why organisations may be tempted to adopt Gen AI. This theory suggests that external factors, such as regulations, norms, and expectations of stakeholders, influence organisations. In the case of Gen AI, organisations are likely to be influenced by stakeholders' expectations, particularly if they feel that their competitors are already using the technology to gain an edge. In addition, the S-O-R (Stimulus-Organism-Response) theory can help organisations identify various stimuli that prompt them to adopt Gen AI. In this context, the organism is the organisation, while the stimulus is the competitive pressure or stakeholder demand. The response is the adoption of Gen AI to gain a competitive advantage.

Organisations can make informed decisions about adopting Gen AI by considering the external factors driving its adoption. Understanding the reasons for adopting Gen AI can help them identify opportunities for growth and innovation while mitigating potential risks and challenges. In addition to answering fundamental questions such as *what*, *why*, and *when*, the

OIPT and stakeholder view can help adopt Gen AI by addressing more specific questions such as *where* and *who*. These theories can help identify the locations and individuals who can play a crucial role in guiding the adoption of Gen AI. For example, OIPT can help organisations understand how information flows within their structure and how they can leverage it to adopt Gen AI. Similarly, stakeholder theory can help them identify key stakeholders and understand their interests and concerns regarding Gen AI, guiding the adoption process more inclusively and ethically.

ROT provides a framework for organisations to allocate and manage their resources effectively. In adopting Gen AI, ROT can be further utilised to answer questions such as *how* and *when* Gen AI can be most effectively integrated into an organisation's operations. By leveraging ROT, organisations can identify the necessary resources and strategies to successfully implement Gen AI and mitigate any potential risks or challenges that may arise during the implementation process.

The success of technology adoption is determined by the technology itself and various factors within and between different levels of an organisation (Premkumar & Ramamurthy, 1995). The UET and RV are two critical theoretical frameworks that explain the significance of intra- and inter-organizational aspects. UET highlights the influence of top-level management on the technology adoption process. At the same time, RV emphasises the importance of relationships and networks among various actors inside and outside the organisation. By considering these intra- and inter-organisational factors, organisations can better comprehend and navigate the complexities of technology adoption.

To facilitate the process of answering significant research questions using theories, we have developed a comprehensive framework designed to help scholars better assimilate the relevant context (see Figure 1). This framework considers six key research questions (see Whetten, 1989) that are particularly important in many academic disciplines and guides how to approach each question systematically and effectively. By following the steps outlined in this framework, researchers can gain a deeper understanding of the underlying theoretical concepts and use this knowledge to develop more insightful and impactful research findings.

Figure 1: Toolbox for the Gen AI adoption (Authors own work)

4. Theoretical Framework

The inputs-process-outputs approach is a theoretical framework that helps identify the factors essential for building Gen AI capabilities and adopting them for benchmarking supply chain management practices. This approach involves identifying the inputs, processes, and outputs necessary to successfully adopt and implement Gen AI in supply chain management. Our study extensively reviewed the literature to identify the specific inputs, processes, and outputs required for benchmarking supply chain management practices using Gen AI. We found that the inputs for building Gen AI capabilities include technology, organisational and institutional factors. At the same time, the processes involve trust building among the partners, collaboration, top management belief and top management participation. The outputs of Gen AI include predictive models, recommendations, and insights that can be used for benchmarking supply chain management practices. Our study uses Gen AI to explain the inputs-process-outputs framework for benchmarking supply chain management practices.

4.1 Inputs

It may be necessary to conduct a study to explore the development of Gen AI as a core capability in organisations. Previous research by Mikalef & Gupta (2021) has used the dynamic capability view (DCV) to explain how AI capabilities can be built by bundling tangible and intangible resources. Gupta & George (2016) and Akter et al. (2016) have also used the DCV to demonstrate how big data analytics can be developed as an organisational capability, leading to improved performance. Dubey et al. (2019) used an integrated approach of the resource-based view (RBV) and institutional theory to show how big data analytics capabilities can enhance performance in manufacturing organisations. Therefore, these theories can be applied to identify the necessary resources, capabilities, or drivers for developing Gen AI capability.

Institutional theory can help us understand the external and internal pressures that compel organisations to adopt Gen AI. Previous studies, such as Liang et al. (2007), have used institutional theory to explain the adoption of ERP. Following criticisms of institutional theory, Liang et al. (2007) integrated institutional theory with upper echelon theory (UET) to address the study's limitations. Similarly, Chakraborty et al. (2023) used the S-O-R framework to explain the adoption of medicine delivery action. In the S-O-R framework, stimulants serve as the drivers or input of the framework. Therefore, we suggest using institutional theory, upper echelon theory, and the S-O-R perspective to guide scholars in developing research hypotheses that explain the factors leading to the adoption of Gen AI (see Figure 2).

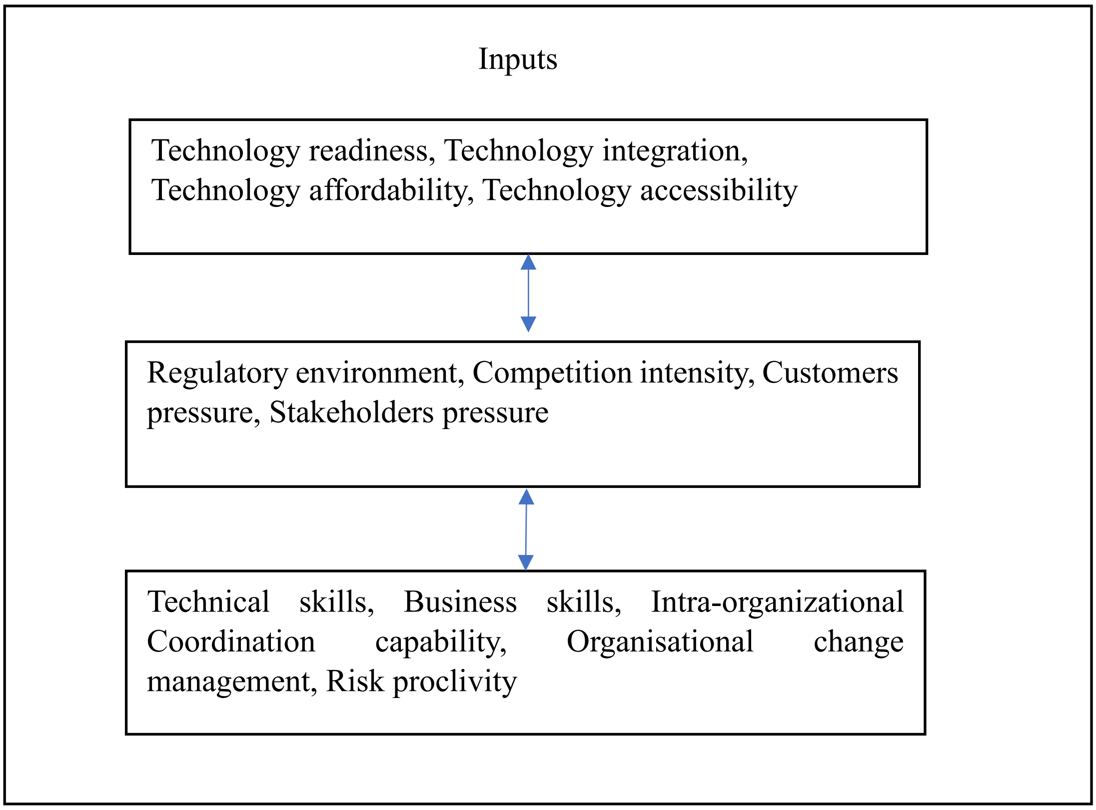

Figure 2: Inputs (factors, drivers, enablers, stimulants)

4.2 Process

This study focuses on understanding how inputs are transformed into a desired outcome. This transformation process can be influenced by various factors, which can either help or hinder it. These factors are known as mediating or moderating factors. This study aims to explore and understand the complex interplay between these factors and their impact on the overall process. Contingency theory explains the contextual factors (see Sousa & Voss, 2008) relevant to the development of Gen AI as an organisational capability or its adoption. While identifying facilitating factors is essential, it is equally crucial to recognise the conditions organisations must create to achieve optimal benefits from Gen AI in benchmarking supply chain practices. Therefore, we present a process view of Gen AI based on these organisational theories (see Figure 3).

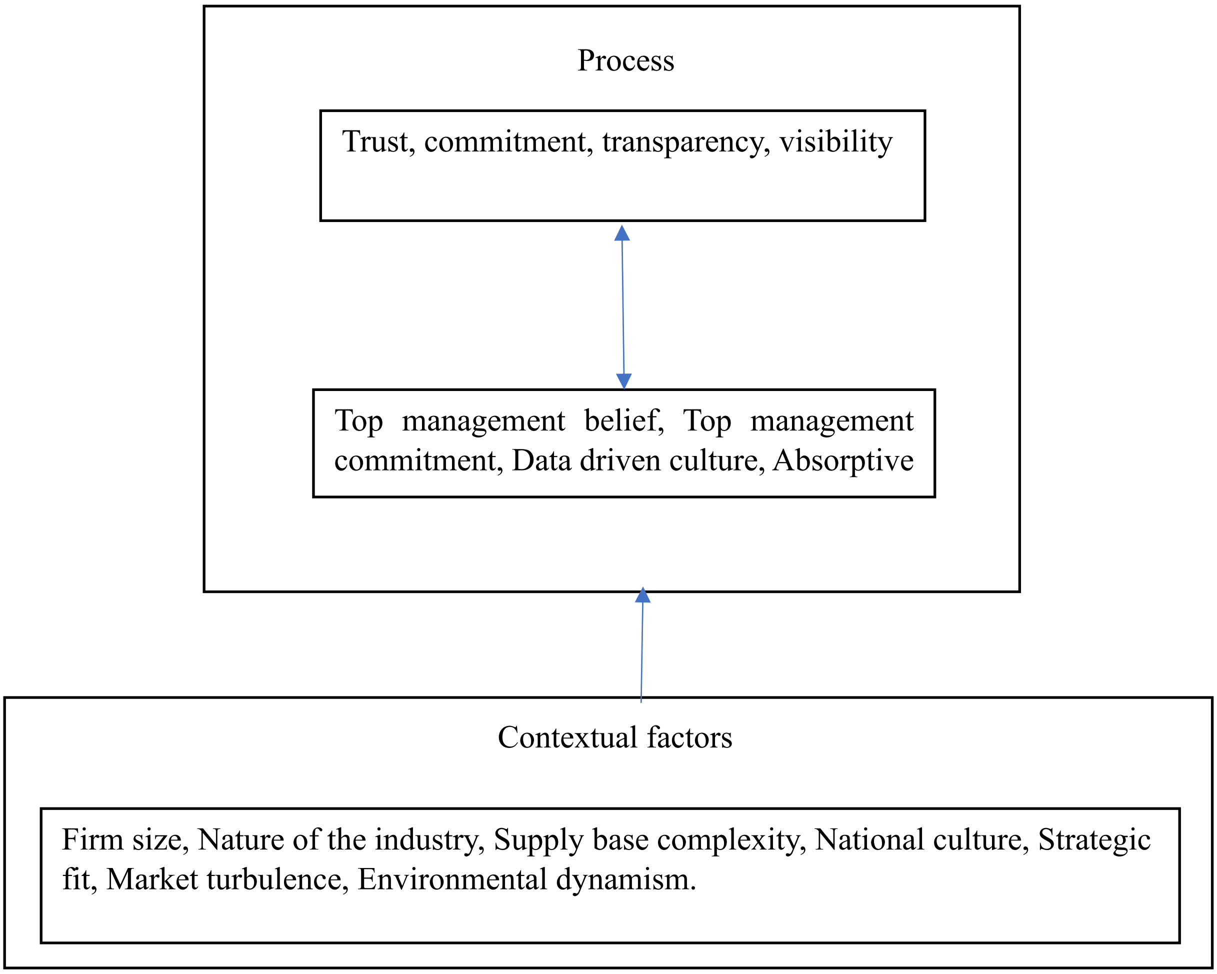

Figure 3: Process (mediators or moderators)

4.3 Outputs

When we transform inputs, the result is known as outputs. The outputs depend on factors like the transformation used, the surrounding environment, and any relevant restrictions or constraints. These factors significantly affect the output, and by carefully considering them, we can better understand the underlying processes. We can achieve better results by optimising our approach based on this understanding. For example, in supply chain management, benchmarking is a valuable technique to identify areas for improvement and optimise the overall process. Gen AI plays a crucial role in this process, as it can simulate different supply chain scenarios and generate outputs based on different conditions. This powerful capability reassures us that we can identify the best method to optimise supply chain management practices and achieve better results (Figure 4). The performance metrics have been categorised based on the SCOR framework.

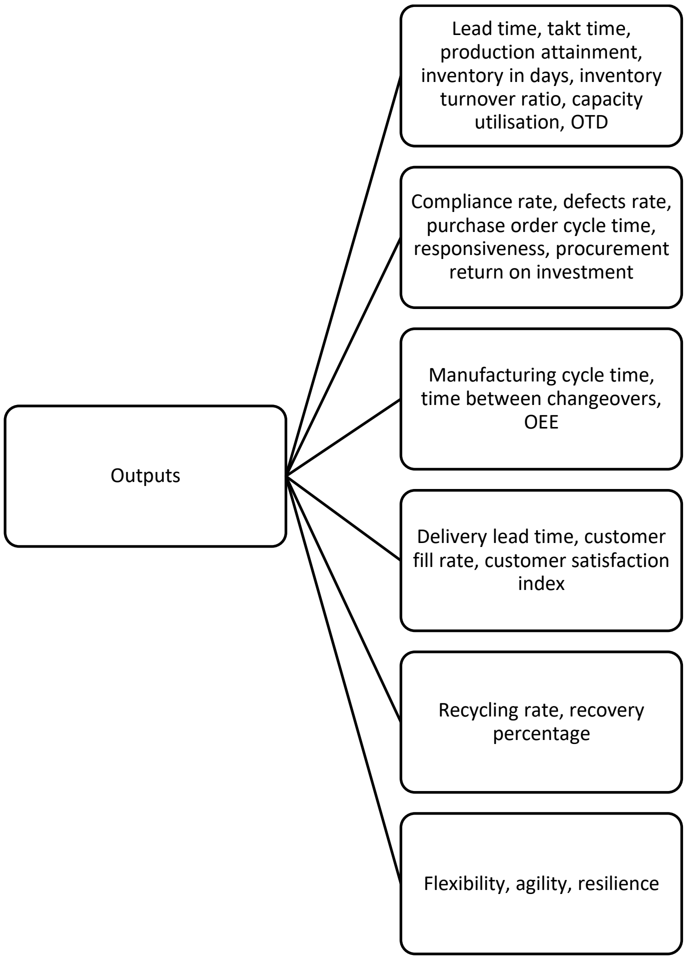

Figure 4: Outputs (Supply Chain Performance)

The input-process-output framework is powerful when developing a theoretical framework for Gen AI. It involves identifying the factors or drivers that contribute to the development of Gen AI and any motivators that prompt organisations to adopt Gen AI. Once these inputs have been identified, the system facilitates the factors to generate the desired outputs. This process is often influenced by mediating or moderating variables that can impact the effect of inputs on outputs. These variables play a significant role in the framework, as they can either enhance or diminish the effect of the inputs on the outputs. In this instance, we are introducing two distinct models for Gen AI. Figure 5 depicts the various factors that could impact an organisation's decision to adopt Gen AI. These factors could be institutional or other motivating factors that influence the adoption of Gen AI. Some factors act as mediating variables, especially those that facilitate the adoption of Gen AI to enhance supply chain performance. Additionally, contextual factors moderate the effect of Gen AI on the supply chain performance.

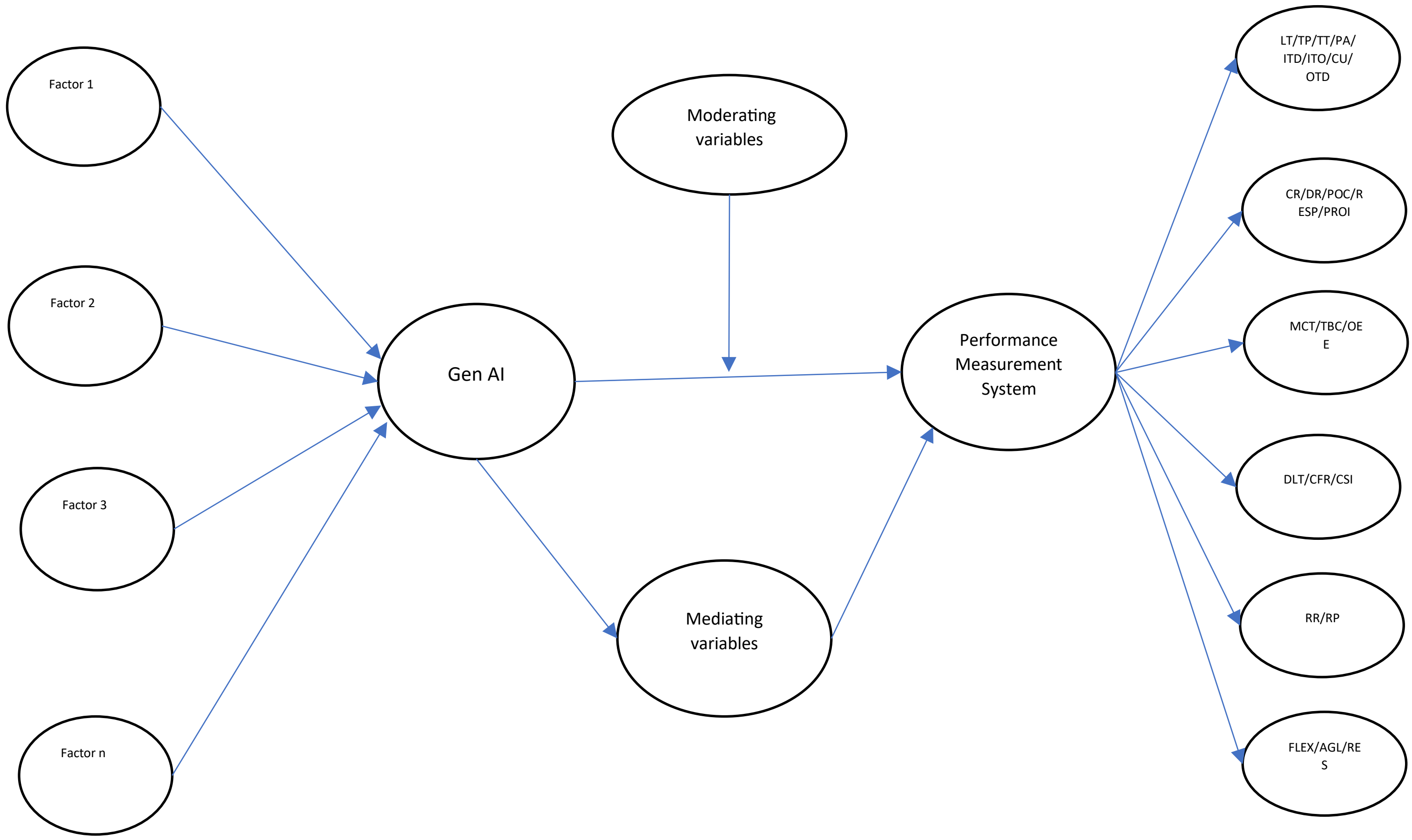

Figure 5: Adoption of Gen AI

Figure 6 depicts the steps taken by the organisation to build Gen AI as an organisational capability. This has been accomplished by utilising the dynamic capability or resource-based view as a framework for developing and implementing this capability. By doing so, the organisation has positioned itself to better leverage its resources and capabilities to create a competitive advantage in the marketplace.

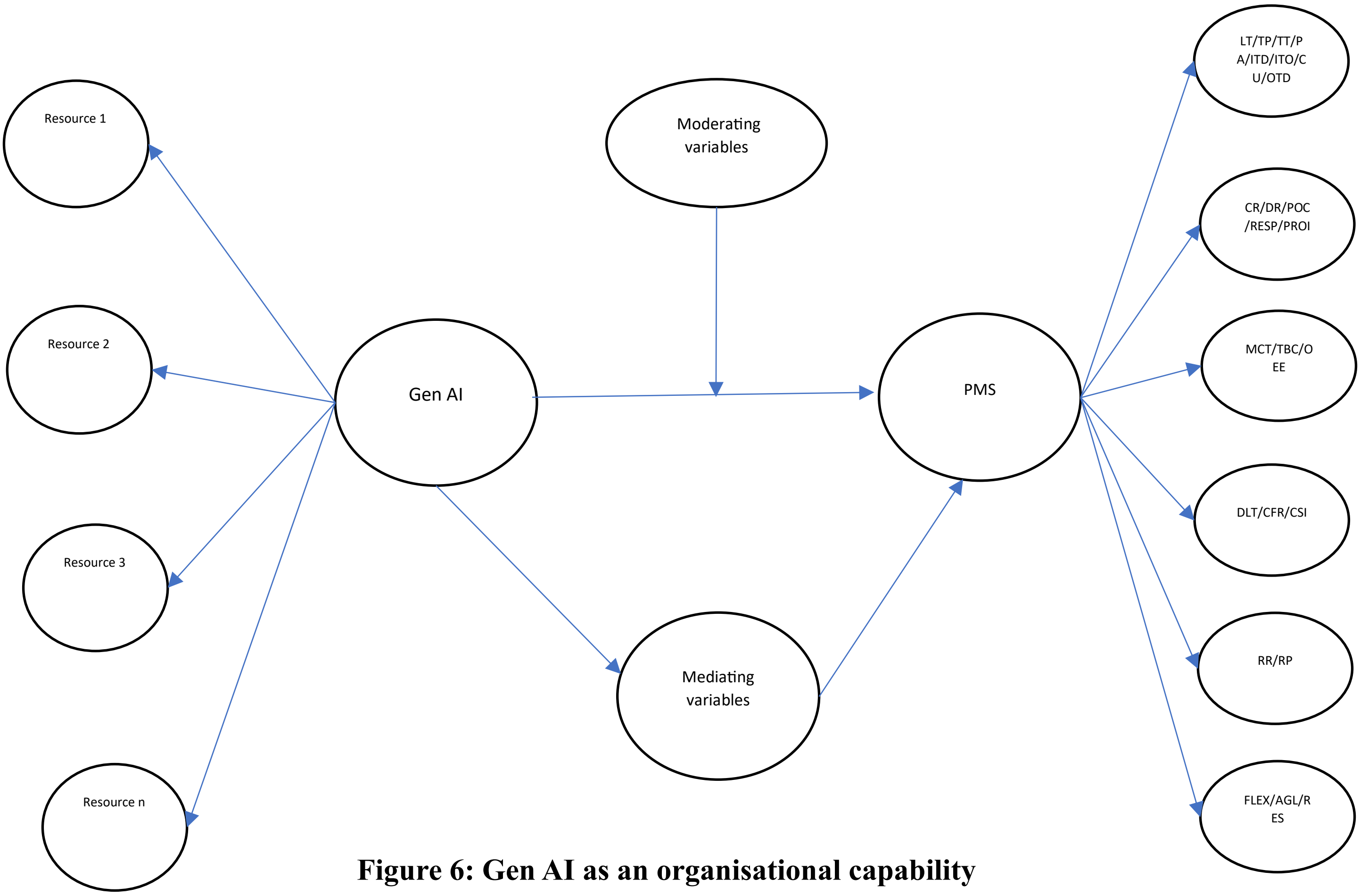

Figure 6: Gen AI as an organisational capability

5. Discussions

Our study provides detailed insights into the critical aspects of Gen AI. It presents six fundamental questions that need to be critically assessed by scholars and practitioners who are working with Gen AI. The six questions we have identified include factors such as ethical considerations, legal and regulatory frameworks, the impact of Gen AI on society, and the potential risks associated with its adoption. We believe these questions are crucial for ensuring that Gen AI is adopted effectively and safely for all stakeholders. Our study offers unique directions and insights to academics and practitioners interested in understanding Gen AI using theoretical frameworks. In conclusion, our research contributes to the growing knowledge of Gen AI and serves as a practical guide for those working with this technology.

5.1 Implications for Scholars

The emergence of Gen AI is a new phenomenon that has created confusion among scholars trying to explore its opportunities. This study aims to provide a comprehensive theoretical toolbox to help academic researchers understand how to adopt Gen AI and gain a competitive advantage. By developing this theoretical foundation, we hope to understand better the factors driving the adoption or development of Gen AI. This research could help organisations develop strategies to manage its adoption effectively. Although most studies have focused on the benefits and challenges of Gen AI, some scholars have conducted exploratory studies to gauge the potential benefits of Gen AI or Chat GPT in operations and supply chain management (see Fosso Wamba et al., 2023a, b).

Currently, there is a lack of research that focuses on theory-driven explanations. This could be due to a lack of clarity on the theoretical front and the availability of data to test these theories. Our contribution aims to fill this gap and provide a useful guide for scholars to understand how Gen AI can improve supply chain management practices. It is important to consider various theories and understand their application in specific situations. Gen AI has generated significant interest in today's dynamic environment due to its potential impact. However, unlike other disruptive technologies, it is crucial to thoroughly analyse the specific contexts in which Gen AI is being adopted to improve supply chain practices effectively. This requires a deep understanding of the roles of leadership and culture, as they play a critical part in successful implementation. Grounded in the Upper Echelons Theory (UET) proposed by Hambrick and Mason (1984), the pivotal role of top management in shaping the organisation's strategies becomes apparent. By leveraging Gen AI's capabilities, top management can streamline the organisation's supply chain strategies, improving efficiency and performance.

However, while leadership is crucial, it is also essential to acknowledge organisational culture's significant impact in fostering stakeholder confidence (Doh & Quigley, 2014). A strong organisational culture can influence stakeholders to trust and rely on Gen AI to guide decisions in complex settings. This is vital for effectively embracing AI technologies. The successful adoption or implementation of Gen AI within an organisation is influenced by technological, organisational, and environmental factors (T-O-E) and contextual factors. Market conditions, regulatory environment, and company culture are crucial in shaping how Gen AI can be leveraged to improve various aspects of the supply chain.

For example, Gen AI can enhance end-to-end visibility by providing real-time insights into inventory levels, demand patterns, and logistics processes. Additionally, it can help build trust among supply chain partners by ensuring data security and transparency. Moreover, Gen AI facilitates collaboration by enabling seamless information sharing and fostering synergies in supply chain activities, ultimately improving supply chain practices. In conclusion, this study aims to provide a theoretical foundation for Gen AI that can help academic researchers understand the adoption of this technology across various contexts. By better understanding the underlying factors driving the adoption of this technology, this research could help organisations manage its adoption effectively.

5.2 Implications for Managers

Managing supply chains has become increasingly complex in today's fast-paced business environment (Sodhi & Son, 2009; Sodhi & Tang, 2021a; Xu et al., 2023a). The COVID-19 pandemic has further amplified this complexity, particularly regarding disruptions in the global supply chain (Sodhi & Tang, 2021b; Xu et al., 2023b). Geopolitical issues such as trade wars and sanctions have also added to the challenges of effectively managing supply chains. Organisations are considering Gen AI as a potential solution to address these challenges. Our theoretical toolbox for Gen AI provides a comprehensive guide for managers interested in exploring the benefits of adopting Gen AI in supply chain management. This toolbox covers various aspects of Gen AI, including its applications, benefits, and limitations. By leveraging the power of Gen AI, organisations can gain valuable insights into their supply chains, such as real-time tracking of goods, demand forecasting, and risk management. This assistance can help managers make informed decisions about inventory management, production planning, and logistics, resulting in increased efficiency and reduced costs. Overall, our theoretical toolbox for Gen AI can serve as an invaluable resource for managers who want to understand the potential of Gen AI in supply chain management. By incorporating Gen AI into their operations, organisations can adapt to the changing business landscape and build resilience in their supply chains. In the global context, the complexity of the supply base, cultural differences, geopolitical crises, and competing goals often create multiple challenges for supply chain managers in planning and execution. The Gen AI application is designed to bridge cultural gaps and provide comprehensive insights into managing the intricate layers of the supply chain and navigating geopolitical uncertainties. Industry leaders such as Toyota, General Mills, AWS, Dell, Ford, Volkswagen, and Sanofi have reaped significant benefits from leveraging Gen AI. As a result, supply chain managers can rely on Gen AI to make informed decisions, particularly in challenging business environments. Hence, using Gen AI to assist in benchmarking supply chain practices within a complex and rapidly changing environment offers an exciting opportunity for supply chain managers. By harnessing the power of AI technology, supply chain managers can gain valuable insights, identify areas for improvement, and make informed decisions to optimise their supply chain operations. This approach allows for more precise and efficient benchmarking and enables adopting proactive strategies to address challenges and capitalise on emerging trends in the ever-evolving supply chain landscape. Despite the significant benefits and applications of Gen AI, it is essential to acknowledge the criticism it has faced due to the potential for producing inaccurate results and the associated security concerns. Such issues need to be carefully considered and addressed when formulating strategies involving the use of Gen AI.

5.3 Future Research Directions

Our analysis shows that the research on Gen AI and its application in supply chain management is still nascent. Although Gen AI has captured considerable attention from scholars and practitioners, much is still to be explored in this field. To further advance research in this area, theory-driven studies could play a crucial role in expanding the scope of the current research. Integrating theories from different domains, such as computer science, psychology, and organisational behaviour, could provide a more comprehensive understanding of the potential impact of Gen AI on supply chain management. In conclusion, while the research on Gen AI and its impact on supply chain management is still in its infancy, there is immense potential for further exploration in this field. By leveraging theory-driven research, we can expand our understanding of this phenomenon and its implications for businesses and society.

We identified ten theories that can be instrumental in scholars gaining a deeper understanding of the benefits of Gen AI for benchmarking supply chain management practices. Gen AI is a powerful tool that enables a comprehensive analysis of the industry's performance in several critical areas. It provides insights into the cash-to-cash conversion cycle (C2C), days of sales outstanding (DSO), days of payable outstanding (DPO), inventory turnover ratio, responsiveness, flexibility, resilience, and many other aspects (Olan et al., 2022). These insights can be derived with the help of a wide range of these ten theories, which allow for a detailed evaluation of various firms' supply chain management practices. By leveraging these theories, scholars can gain a more nuanced understanding of the strengths and weaknesses of different organisations, which can help them identify best practices and areas for improvement. Overall, using Gen AI and these ten theories can be a valuable tool for scholars and practitioners alike in supply chain management.

6. Conclusion

In recent times, there has been a significant increase in interest and discussions around the application of Gen AI across various fields. However, scholars must engage in critical theory-driven research to test all the assumptions made so far. There is a need to assess the critical usefulness of Gen AI, particularly in terms of benchmarking supply chain management practices. To achieve this, scholars must focus on understanding the usefulness of different theories and their boundary conditions. This will help to evaluate the extent to which Gen AI can be relied upon to improve supply chain management practices. It is essential to note that theory-driven research is vital to properly understand the potential applications of Gen AI in supply chain management. This type of research helps to identify the limitations of different theories and how they can be applied to real-world situations. By undertaking this critical research, scholars can analyse the effectiveness of Gen AI in improving supply chain management practices, identify potential challenges and limitations, and develop frameworks to overcome them. In conclusion, raising awareness about theory-driven research is essential to understanding Gen AI and its potential applications in supply chain management. By conducting such research, we can assess the critical usefulness of Gen AI and develop strategies to improve supply chain management practices.

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References

Abu Huson, Y., Sierra-García, L., & Garcia-Benau, M. A. (2024). A bibliometric review of information technology, artificial intelligence, and blockchain on auditing. *Total Quality Management & Business Excellence*, *35*(1-2), 91-113.

Adebanjo, D., Abbas, A., & Mann, R. (2010). An investigation of the adoption and implementation of benchmarking. *International Journal of Operations & Production Management*, 30(11), 1140–1169.

Akhtar, P., Ghouri, A. M., Ashraf, A., Lim, J. J., Khan, N. R., & Ma, S. (2024). Smart product platforming powered by AI and Generative AI: Personalization for the circular economy. *International Journal of Production Economics*, *273*, 109283.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?". *International Journal of Production Economics*, 182, 113-131.

Almazmomi, N., Ilmudeen, A., & Qaffas, A. A. (2022). The impact of business analytics capability on data-driven culture and exploration: achieving a competitive advantage", *Benchmarking: An International Journal*, 29(4), 1264-1283.

Alsharhan, A., Al-Emran, M., & Shaalan, K. (2024). Chatbot adoption: A multiperspective systematic review and future research agenda. *IEEE Transactions on Engineering Management*, 71, 10232-10244.

AL-Shboul, M. D. A., Garza-Reyes, J. A., & Kumar, V. (2018). Best supply chain management practices and high-performance firms: The case of Gulf manufacturing firms. *International Journal of Productivity and Performance Management*, 67 (9), 1482-1509.

Amaya, J., & Holweg, M. (2024). Using algorithms to improve knowledge work. *Journal of Operations Management,* 70(3), 482-513.

Anand, G., & Kodali, R. (2008). Benchmarking the benchmarking models. *Benchmarking: An International Journal*, 15(3), 257-291.

Andersen, B., Fagerhaug, T., Randmæl, S., Schuldmaier, J., & Prenninger, J. (1999). Benchmarking supply chain management: finding best practices. *Journal of Business & Industrial Marketing*, 14 (5/6), 378-389.

Aragón-Correa, J. A., & Sharma, S. (2003). A contingent resource-based view of proactive corporate environmental strategy. *Academy of Management Review*, 28 (1), 71-88.

Arsenyan, J., & Piepenbrink, A. (2024). Artificial intelligence research in management: A computational literature review. *IEEE Transactions on Engineering Management*, *71*, 5088-5100.

Arzu Akyuz, G., & Erman Erkan, T. (2010). Supply chain performance measurement: a literature review. *International Journal of Production Research*, 48 (17), 5137-5155.

Asrofah, T., Zailani, S., & Fernando, Y. (2010). Best practices for the effectiveness of benchmarking in the Indonesian manufacturing companies. *Benchmarking: An International Journal*, 17(1), 115-143.

Astley, W. G., & Van de Ven, A. H. (1983). Central perspectives and debates in organization theory. *Administrative Science Quarterly*, 28(2), 245–273.

Avdiji, H., Elikan, D., Missonier, S., & Pigneur, Y. (2020). A design theory for visual inquiry tools. *Journal of the Association for Information Systems*, 21, 695-735.

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, *163*, 120420.

Bag, S., Rahman, M. S., Srivastava, G., Giannakis, M., & Foropon, C. (2023). Data-driven digital transformation and the implications for antifragility in the humanitarian supply chain. *International Journal of Production Economics*, *266*, 109059.

Bag, S., Gupta, S., Chan, H. L., & Kumar, A. (2024). Building smart product-service systems capabilities for circular supply chains in the Industry 4.0 era. *Transportation Research Part E: Logistics and Transportation Review*, *188*, 103625.

Bagchi, P. K. (1996). Role of benchmarking as a competitive strategy: the logistics experience. *International Journal of Physical Distribution & Logistics Management*, 26(2), 4–22.

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. *Electronic Markets*, 33 (1), 1-17.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120.

Bartlett, C. A., & Ghoshal, S. (1994). Changing the role of top management: Beyond strategy to purpose. *Harvard Business Review*, 72 (6), 79–88.

Beamon, B. M. (1999). Measuring supply chain performance. *International Journal of Operations & Production Management*, 19(3), 275–292.

Bensaou, M., & Venkatraman, N. (1995). Configurations of interorganizational relationships: A comparison between US and Japanese automakers. *Management Science*, 41(9), 1471-1492.

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management*, 50(3), 55–73.

Bendoly, E., Chandrasekaran, A., Lima, M. D. R. F., Handfield, R., Khajavi, S. H., & Roscoe, S. (2023). The role of generative design and additive manufacturing capabilities in developing human–AI symbiosis: Evidence from multiple case studies. *Decision Sciences*. DOI: 10.1111/deci.12619.

Butt, A., Imran, F., Helo, P., & Kantola, J. (2024). Strategic design of culture for digital transformation. *Long Range Planning*, *57*(2), 102415.

Cannas, V. G., Ciano, M. P., Saltalamacchia, M., & Secchi, R. (2024). Artificial intelligence in supply chain and operations management: a multiple case study research. *International Journal of Production Research*, *62*(9), 3333-3360.

Carpenter, M. A., Geletkanycz, M. A., & Sanders, W. G. (2004). Upper echelons research revisited: Antecedents, elements, and consequences of top management team composition. *Journal of Management*, 30(6), 749-778.

CDO Magazine Bureau (2024). Volkswagen Unveils New AI Lab to Make Cars Smarter. https://www.cdomagazine.tech/aiml/volkswagen-unveils-new-ai-lab-to-make-cars-smarter (Date of Access: 18 February, 2024).

Chakraborty, D., Singu, H. B., Kar, A. K., & Biswas, W. (2023). From fear to faith in the adoption of medicine delivery application: an integration of SOR framework and IRT theory. *Journal of Business Research*, 166, 114140.

Chen, S., Meng, Q., & Choi, T. M. (2022). Transportation research Part E-logistics and transportation review: 25 years in retrospect. *Transportation Research Part E: Logistics and Transportation Review*, 161, 102709.

Choi, T. M., Cheng, T. C. E., & Zhao, X. (2016). Multi-methodological research in operations management. *Production and Operations Management*, *25*(3), 379-389.

Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations management*, *27*(10), 1868-1883.

Choi, T. M., Guo, S., & Luo, S. (2020). When blockchain meets social-media: Will the result benefit social media analytics for supply chain operations management?. *Transportation Research Part E: Logistics and Transportation Review*, *135*, 101860.

Choi, T. M. (2021a). Risk analysis in logistics systems: A research agenda during and after the COVID-19 pandemic. *Transportation Research Part E: Logistics and Transportation Review*, 145, 102190.

Choi, T. M. (2021b). Facing market disruptions: values of elastic logistics in service supply chains. *International Journal of Production Research*, *59*(1), 286-300.

Choi, T. M., Kumar, S., Yue, X., & Chan, H. L. (2022). Disruptive technologies and operations management in the Industry 4.0 era and beyond. *Production and Operations Management*, *31*(1), 9-31.

Craighead, C. W., Ketchen Jr, D. J., & Darby, J. L. (2020). Pandemics and supply chain management research: toward a theoretical toolbox. *Decision Sciences*, 51(4), 838-866.

Csaszar, F. A., & Ostler, J. (2020). A contingency theory of representational complexity in organizations. *Organization Science*, 31(5), 1198-1219.

Cushman, R., Malladi, K., & Graefe, M. (2023). How generative AI is revolutionizing supply chain operations (https://www.ibm.com/blog/how-generative-ai-is-revolutionizing-supply-chain-operations/) (Date of access: 16 February 2024).

Dash, A., Ye, J., Wang, G., & Jin, H. (2022). High resolution solar image generation using generative adversarial networks. *Annals of Data Science*. DOI: 10.1007/s40745-022-00436-2.

de Camargo Fiorini, P., Seles, B. M. R. P., Jabbour, C. J. C., Mariano, E. B., & de Sousa Jabbour, A. B. L. (2018). Management theory and big data literature: From a review to a research agenda. *International Journal of Information Management*, *43*, 112-129.

Dhamija, P., & Bag, S. (2020). Role of artificial intelligence in operations environment: a review and bibliometric analysis. *The TQM Journal*, *32*(4), 869-896.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147-160.

Doh, J. P., & Quigley, N. R. (2014). Responsible leadership and stakeholder management: Influence pathways and organizational outcomes. *Academy of Management Perspectives*, *28*(3), 255–274.

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture. *British Journal of Management*, 30(2), 341-361.

Dubey, R., Gunasekaran, A., Bryde, D. J., Dwivedi, Y. K., & Papadopoulos, T. (2020). Blockchain technology for enhancing swift-trust, collaboration and resilience within a humanitarian supply chain setting. *International Journal of Production Research*, 58(11), 3381-3398.

Dubey, R., Gunasekaran, A., Childe, S. J., Fosso Wamba, S., Roubaud, D., & Foropon, C. (2021). Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. *International Journal of Production Research*, 59(1), 110–128.

Dutta, S., & Steinberg,G. (2023). *How Supply Chain Benefits from using generative AI* (https://www.ey.com/en_us/coo/how-generative-ai-in-supply-chain-can-drive-value). (Date of access: 21 February 2024)

Dutta, P., Choi, T. M., Somani, S., & Butala, R. (2020). Blockchain technology in supply chain operations: Applications, challenges and research opportunities. *Transportation Research part E: Logistics and Transportation Review*, 142, 102067.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642.

Dyer, J. H., & Singh, H. (1998). The relational view: Cooperative strategy and sources of interorganizational competitive advantage. *Academy of Management Review*, 23 (4), 660–679.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: what are they?", *Strategic Management Journal*, 21 (10-11), 1105–1121.

Fainshmidt, S., Pezeshkan, A., Lance Frazier, M., Nair, A., & Markowski, E. (2016). Dynamic capabilities and organizational performance: a meta-analytic evaluation and extension. *Journal of Management Studies*, 53 (8), 1348–1380.

Fawcett, S. E., Wallin, C., Allred, C., & Magnan, G. (2009). Supply chain information-sharing: benchmarking a proven path. *Benchmarking: An International Journal*, 16 (2), 222-246.

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative ai. *Business & Information Systems Engineering*, *66*(1), 111-126.

Fosso Wamba, S., Queiroz, M. M., Jabbour, C. J. C., & Shi, C. V. (2023a). Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence?. *International Journal of Production Economics*, 265, 109015.

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2023b). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*. DOI: 10.1080/00207543.2023.2294116.

Freeman, R. E. (1984). *Strategic management: A stakeholder approach*", Pitman: Boston.

Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 4(3), 28–36.

Garcia-Buendia, N., Kristensen, T. B., Moyano-Fuentes, J., & Maqueira-Marín, J. M. (2024). Performance measurement of lean supply chain management: a balanced scorecard proposal. *Production Planning & Control*, *35*(6), 618-638.

Gattiker, T. F. (2007). Enterprise resource planning (ERP) systems and the manufacturing–marketing interface: an information-processing theory view. *International Journal of Production Research*, 45 (13), 2895-2917.

Geletkanycz, M. A. (1997). The salience of 'culture's consequences: The effects of cultural values on top executive commitment to the status quo. *Strategic Management Journal*, 18 (8), 615-634.

Ghobakhloo, M., Fathi, M., Iranmanesh, M., Vilkas, M., Grybauskas, A., & Amran, A. (2024). Generative artificial intelligence in manufacturing: opportunities for actualizing Industry 5.0 sustainability goals. *Journal of Manufacturing Technology Management*, *35*(9), 94-121.

Grimes, M., Von Krogh, G., Feuerriegel, S., Rink, F., & Gruber, M. (2023). From scarcity to abundance: Scholars and scholarship in an age of generative artificial intelligence. *Academy of Management Journal*, *66*(6), 1617-1624.

Grover, V. (1993). An empirically derived model for the adoption of customer-based interorganizational systems. *Decision Sciences*, 24 (3), 603–640.

Guan, J. C., Yam, R. C., Mok, C. K., & Ma, N. (2006). A study of the relationship between competitiveness and technological innovation capability based on DEA models. *European Journal of Operational Research*, 170 (3), 971-986.

Gupta, S., Modgil, S., Meissonier, R., & Dwivedi, Y. K. (2024). Artificial intelligence and information system resilience to cope with supply chain disruption. *IEEE Transactions on Engineering Management*, 71, 10496-10506.

Guillot, R., Dubey, R., & Kumari, S. (2024). B2B supply chain risk measurement systems: a SCOR perspective. *Journal of Business & Industrial Marketing*, *39*(3), 553-567.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability", *Information & Management*, 53 (8), 1049–1064.

Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. *International Journal of Production Economics*, 87(3), 333–347.

Gunasekaran, A., & Kobu, B. (2007). Performance measures and metrics in logistics and supply chain management: a review of recent literature (1995–2004) for research and applications. *International Journal of Production Research*, 45 (12), 2819-2840.

Gunasekaran, A., Dubey, R., Fosso Wamba, S., Papadopoulos, T., Hazen, B. T., & Ngai, E. W. (2018). Bridging humanitarian operations management and organisational theory. *International Journal of Production Research*, 56(21), 6735-6740.

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, 9 (2), 193-206.

Hardy, C., Lawrence, T. B., & Grant, D. (2005). Discourse and collaboration: The role of conversations and collective identity. *Academy of Management Review*, 30 (1), 58-77.

Helo, P., & Hao, Y. (2022). Artificial intelligence in operations management and supply chain management: An exploratory case study. *Production Planning & Control*, *33*(16), 1573-1590.

Hitt, M. A., Xu, K., & Carnes, C. M. (2016). Resource based theory in operations management research", *Journal of Operations Management*, 41, 77-94.

Hughes, P., Hodgkinson, I. R., Elliott, K., & Hughes, M. (2018). Strategy, operations, and profitability: the role of resource orchestration. *International Journal of Operations & Production Management*, 38 (4), 1125–1143.

Ivanov, D. (2024a). Digital supply chain management and technology to enhance resilience by building and using end-to-end visibility during the COVID-19 pandemic. *IEEE Transactions on Engineering Management*, 71, 10485–10495.

Ivanov, D. (2024b). Cash flow dynamics in the supply chain during and after disruptions. *Transportation Research Part E: Logistics and Transportation Review*, *185*, 103526.

Jackson, I., & Ivanov, D. (2023). A beautiful shock? Exploring the impact of pandemic shocks on the accuracy of AI forecasting in the beauty care industry. *Transportation Research Part E: Logistics and Transportation Review*, 180, 103360.

Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation. *International Journal of Production Research*. DOI: 10.1080/00207543.2024.2309309.

Jones, T. M., Felps, W., & Bigley, G. A. (2007). Ethical theory and stakeholder-related decisions: The role of stakeholder culture. *Academy of Management Review*, 32 (1), 137-155.

Kamble, S. S., & Gunasekaran, A. (2020). Big data-driven supply chain performance measurement system: a review and framework for implementation", *International Journal of Production Research*, 58 (1), 65-86.

Kaplan, R. S., & Norton, D. P. (1992). The balanced scorecard: measures that drive performance", *Harvard Business Review*, 70 (1), 71–79.

Ketchen Jr, D. J., & Hult, G. T. M. (2007). Bridging organization theory and supply chain management: The case of best value supply chains. *Journal of Operations Management*, 25 (2), 573-580.

Kala, K., & Sodhi, M. S. (2023). Note: Demonstrating analytics in a low-tech context–truck-routing for solid-waste collection in an Indian metropolis. *Transportation Research Part E: Logistics and Transportation Review*, 176, 103219.

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2024). The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, *18*(4), 1189-1220.

Kar, A. K., Varsha, P. S., & Rajan, S. (2023). Unravelling the impact of generative artificial intelligence (GAI) in industrial applications: A review of scientific and grey literature. *Global Journal of Flexible Systems Management*, 24 (4), 659-689.

Kauppi, K. (2013). Extending the use of institutional theory in operations and supply chain management research: Review and research suggestions. *International Journal of Operations & Production Management*, 33 (10), 1318–1345.

Ketchen Jr, D. J., & Hult, G. T. M. (2007). Bridging organization theory and supply chain management: The case of best value supply chains. *Journal of Operations Management*, 25 (2), 573-580.

Ketter, W., Peters, M., Collins, J., & Gupta, A. (2016). Competitive benchmarking. *MIS Quarterly*, *40*(4), 1057-1080.

Kumar, S., Mookerjee, V., & Shubham, A. (2018). Research in operations management and information systems interface. *Production and Operations Management*, *27*(11), 1893-1905.

Kuo, H. T., & Choi, T. M. (2024). Metaverse in transportation and logistics operations: An AI-supported digital technological framework. *Transportation research part E: Logistics and Transportation Review*, *185*, 103496.

Lambert, D. M., & Enz, M. G. (2017). Issues in supply chain management: Progress and potential. *Industrial Marketing Management*, *62*, 1-16.

Latunreng, W., & Nasirin, C. (2019). Competitive advantage: Exploring the role of partnership with suppliers, customer relationship and information sharing as antecedents", *Journal of Supply Chain Management*, 8 (1), 404-411.

Le, T. T., & Behl, A. (2024). Linking Artificial Intelligence and Supply Chain Resilience: Roles of Dynamic Capabilities Mediator and Open Innovation Moderator. *IEEE Transactions on Engineering Management*, 71, 8577-8590.

Li, S., Ragu-Nathan, B., Ragu-Nathan, T. S., & Rao, S. S. (2006). The impact of supply chain management practices on competitive advantage and organizational performance. *Omega*, 34 (2), 107-124.

Lim, A. F., Lee, V. H., Foo, P. Y., Ooi, K. B., & Wei–Han Tan, G. (2022). Unfolding the impact of supply chain quality management practices on sustainability performance: an artificial neural network approach.*Supply Chain Management: An International Journal*, 27 (5), 611-624.

Lima-Junior, F. R., & Carpinetti, L. C. R. (2019). Predicting supply chain performance based on SCOR® metrics and multilayer perceptron neural networks. *International Journal of Production Economics*, 212, 19-38.

Liu, H., Wei, S., Ke, W., Wei, K. K., & Hua, Z. (2016). The configuration between supply chain integration and information technology competency: A resource orchestration perspective. *Journal of Operations Management*, 44, 13-29.

Liu, W., Choi, T. M., Niu, X., Zhang, M., & Fan, W. (2022). Determinants of business resilience in the restaurant industry during the COVID-19 pandemic: a textual analytics study on an O2O platform case. *IEEE Transactions on Engineering Management*, 71, 10427-10440.

Lockamy, A., & McCormack, K. (2004). Linking SCOR planning practices to supply chain performance: An exploratory study. *International Journal of Operations & Production Management*, 24 (12), 1192–1218.

Maestrini, V., Luzzini, D., Maccarrone, P., & Caniato, F. (2017). Supply chain performance measurement systems: A systematic review and research agenda. *International Journal of Production Economics*, 183, pp. 299-315.

Magd, H., & Curry, A. (2003). Benchmarking: achieving best value in public-sector organisations. *Benchmarking: An International Journal*, 10 (3), 261-286.

Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research*, 175, 114542.

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology.* The MIT Press: USA.

Menhat, M., Yusuf, Y., Gunasekaran, A., & Mohammad, A. M. (2023). Performance measurement framework for the oil and gas supply chain. *Benchmarking: An International Journal*, *30*(9), 3168-3193.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58 (3), 103434.

Miles, R. E., Snow, C. C., Meyer, A. D., & Coleman Jr, H. J. (1978). Organizational strategy, structure, and process. *Academy of Management Review*, *3*(3), 546-562.

Mithas, S., Ramasubbu, N., & Sambamurthy, V. (2011). How information management capability influences firm performance. *MIS Quarterly*, 35 (1), 237–256.

Mithas, S., Chen, Z. L., Saldanha, T. J., & De Oliveira Silveira, A. (2022). How will artificial intelligence and Industry 4.0 emerging technologies transform operations management?. *Production and Operations Management*, *31*(12), 4475-4487.

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing*, 58 (3), 20–38.

Moshtari, M. (2016). Inter-organizational fit, relationship management capability, and collaborative performance within a humanitarian setting. *Production and Operations Management*, 25 (9), 1542–1557.

Munir, M., Jajja, M. S. S., & Chatha, K. A. (2022). Capabilities for enhancing supply chain resilience and responsiveness in the COVID-19 pandemic: exploring the role of improvisation, anticipation, and data analytics capabilities. *International Journal of Operations & Production Management*, *42*(10), 1576-1604.

Norton, S. (2024). General Mills Lays The Foundation For An AI-Driven Future. https://www.forbes.com/sites/stevennorton/2024/03/04/general-mills-lays-the-foundation-for-an-ai-driven-future/ (Data of access: 5 June 2024).

Oliver, C. (1997). Sustainable competitive advantage: combining institutional and resource-based views. *Strategic Management Journal*, 18 (9), 697-713.

Olan, F., Arakpogun, E. O., Jayawickrama, U., Suklan, J., & Liu, S. (2022). Sustainable supply chain finance and supply networks: The role of artificial intelligence. *IEEE Transactions on Engineering Management*. DOI: 10.1109/TEM.2021.3133104.

Ooi, K. B., Tan, G. W. H., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., ... & Wong, L. W. (2023). The potential of generative artificial intelligence across disciplines: perspectives and future directions. *Journal of Computer Information Systems*, DOI: 10.1080/08874417.2023.2261010.

Parmar, B. L., Freeman, R. E., Harrison, J. S., Wicks, A. C., Purnell, L., & De Colle, S. (2010). Stakeholder theory: The state of the art. *Academy of Management Annals*, 4 (1), 403–445.

Partington, D. (2000). Building grounded theories of management action. *British Journal of Management*, 11 (2), 91–102.

Patterson, K. A., Grimm, C. M., & Corsi, T. M. (2003). Adopting new technologies for supply chain management. *Transportation Research Part E: Logistics and Transportation Review*, 39 (2), 95-121.

Peng Wong, W., & Yew Wong, K. (2008). A review on benchmarking of supply chain performance measures. *Benchmarking: An International Journal*, 15 (1), 25-51.

Peng, M. W., Sun, S. L., Pinkham, B., & Chen, H. (2009). The institution-based view as a third leg for a strategy tripod. *Academy of Management Perspectives*, 23 (3), 63-81.

Pfeffer, J., & Salancik, G. R. (1977). Organization design: The case for a coalitional model of organizations. *Organizational Dynamics*, *6*(2), 15-29.

Premkumar, G., & Ramamurthy, K. (1995). The role of interorganizational and organizational factors on the decision mode for adoption of interorganizational systems. *Decision Sciences*, 26 (3), 303-336.

Queiroz, M. M., Wamba, S. F., Jabbour, C. J. C., & Machado, M. C. (2022). Supply chain resilience in the UK during the coronavirus pandemic: a resource orchestration perspective. *International Journal of Production Economics*, 245, 108405.

Reynolds, S. J., Schultz, F. C., & Hekman, D. R. (2006). Stakeholder theory and managerial decision-making: Constraints and implications of balancing stakeholder interests. *Journal of Business Ethics*, 64, 285–301.

Richey Jr, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, 44 (4), 532–549.

Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T., & Ivanov, D. (2023). A review on reinforcement learning algorithms and applications in supply chain management. *International Journal of Production Research*, 61 (20), 7151-7179.

Sætra, H. S. (2023). Generative AI: Here to stay, but for good?", *Technology in Society*, 75, 102372.

Sarkis, J., Zhu, Q., & Lai, K. H. (2011). An organizational theoretic review of green supply chain management literature. *International Journal of Production Economics*, 130 (1), 1-15.

Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *Academy of Management Annals*, 12 (1), 390-439.

Schulze, J., & Krumm, S. (2017). The "virtual team player" A review and initial model of knowledge, skills, abilities, and other characteristics for virtual collaboration. *Organizational Psychology Review*, 7 (1), 66-95.

Sellitto, M. A., Pereira, G. M., Borchardt, M., Da Silva, R. I., & Viegas, C. V. (2015). A SCOR-based model for supply chain performance measurement: application in the footwear industry. *International Journal of Production Research*, 53 (16), 4917-4926.

Sharma, P., Tiwari, S., Choi, T. M., & Kaul, A. (2024). Big data analytics for crisis management from an information processing theory perspective: A multimethodological study. *IEEE Transactions on Engineering Management*, 71, 10585-10599.

Shore, A., Tiwari, M., Tandon, P., & Foropon, C. (2024). Building entrepreneurial resilience during crisis using generative AI: An empirical study on SMEs. *Technovation*, *135*, 103063.

Sirmon, D. G., Hitt, M. A., Ireland, R. D., & Gilbert, B. A. (2011). Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects. *Journal of Management*, 37 (5), 1390–1412.

Sodhi, M. S., & Son, B. G. (2009). Supply-chain partnership performance. *Transportation Research Part E: Logistics and Transportation Review*, *45*(6), 937-945.

Sodhi, M. S. (2015). Conceptualizing social responsibility in operations via stakeholder resource-based view. *Production and Operations Management*, *24*(9), 1375-1389.

Sodhi, M. S., & Tang, C. S. (2021a). Extending AAA capabilities to meet PPP goals in supply chains. *Production and Operations Management*, *30*(3), 625-632.

Sodhi, M. S., & Tang, C. S. (2021b). Supply chain management for extreme conditions: Research opportunities. *Journal of Supply Chain Management*, *57*(1), 7-16.

Soni, G., & Kodali, R. (2010). Internal benchmarking for assessment of supply chain performance. *Benchmarking: An International Journal*, 17 (1), 44-76.

Sousa, R., & Voss, C. A. (2008). Contingency research in operations management practices. *Journal of Operations Management*, 26 (6), 697-713.

Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, 27 (10), 1849-1867.

Stark, A., Ferm, K., Hanson, R., Johansson, M., Khajavi, S., Medbo, L., ... & Holmström, J. (2023). Hybrid digital manufacturing: Capturing the value of digitalization. *Journal of Operations Management*, *69*(6), 890-910.

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The Janus effect of generative AI: Charting the path for responsible conduct of scholarly activities in information systems. *Information Systems Research*, *34*(2), 399-408.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18 (7), 509-533.

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28 (13), 1319–1350.

Tiwari, M., Bryde, D. J., Stavropoulou, F., & Malhotra, G. (2024a). Understanding the evolution of flexible supply chain in the business-to-business sector: a resource-based theory perspective. *International Studies of Management & Organization*, DOI: 10.1080/00208825.2024.2324245.

Tiwari, M., Bryde, D. J., Stavropolou, F., Dubey, R., Kumari, S., & Foropon, C. (2024b). Modelling supply chain Visibility, digital Technologies, environmental dynamism and healthcare supply chain Resilience: An organisation information processing theory perspective. *Transportation Research Part E: Logistics and Transportation Review*, *188*, 103613.

Toyota Newsroom (2023). https://pressroom.toyota.com/toyota-research-institute-unveils-new-generative-ai-technique-for-vehicle-design/. Date of Access: 30 June 2024.

Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *Academy of Management Review*, 3 (3), 613–624.

Upadhyay, N., & Kamble, A. (2023). Examining Indian consumer pro-environment purchase intention of electric vehicles: Perspective of stimulus-organism-response. *Technological Forecasting and Social Change*, 189, 122344.

Volberda, H. W., Van Der Weerdt, N., Verwaal, E., Stienstra, M., & Verdu, A. J. (2012), Contingency fit, institutional fit, and firm performance: A metafit approach to organization–environment relationships. *Organization Science*, 23 (4), 1040–1054.

Wang, L., Huang, N., Hong, Y., Liu, L., Guo, X., & Chen, G. (2023). Voice-based AI in call center customer service: A natural field experiment. *Production and Operations Management*, *32*(4), 1002-1018.

Warschauer, M. (2004). *Technology and social inclusion: Rethinking the digital divide*. MIT Press: USA.

Weick, K. E. (1989). Theory construction as disciplined imagination. *Academy of Management Review*, 14 (4), 516–531.

Whetten, D. A. (1989). What constitutes a theoretical contribution?”, *Academy of Management Review*, 14 (4), 490–495.

Willmington, C., Belardi, P., Murante, A. M., & Vainieri, M. (2022). The contribution of benchmarking to quality improvement in healthcare. A systematic literature review. *BMC Health Services Research*, 22 (1), 1–20.

Xu, J., Pero, M. E. P., Ciccullo, F., & Sianesi, A. (2021). On relating big data analytics to supply chain planning: towards a research agenda. *International Journal of Physical Distribution & Logistics Management*, 51 (6), 656-682.

Xu, X., Sethi, S. P., Chung, S. H., & Choi, T. M. (2023a). Reforming global supply chain management under pandemics: The GREAT-3Rs framework. *Production and Operations Management*, *32*(2), 524-546.

Xu, X., Siqin, T., Chung, S. H., & Choi, T. M. (2023b). Seeking survivals under COVID-19: The WhatsApp platform's shopping service operations. *Decision Sciences*, *54*(4), 375-393.

Yanow, D. (2012). Organizational ethnography between toolbox and world-making. *Journal of Organizational Ethnography*, 1 (1), 31–42.

Yan, Y., Chow, A. H., Ho, C. P., Kuo, Y. H., Wu, Q., & Ying, C. (2022). Reinforcement learning for logistics and supply chain management: Methodologies, state of the art, and future opportunities. *Transportation Research Part E: Logistics and Transportation Review*, 162, 102712.

Yu, Y., Lakemond, N., & Holmberg, G. (2024). AI in the context of complex intelligent systems: Engineering management consequences. *IEEE transactions on engineering management*, *71*, 6512-6525.

Yusuf, Y. Y., Gunasekaran, A., Musa, A., Dauda, M., El-Berishy, N. M., & Cang, S. (2014). A relational study of supply chain agility, competitiveness and business performance in the oil and gas industry. *International Journal of Production Economics*, *147*, 531-543.

Zairi, M. (1992). The art of benchmarking: using customer feedback to establish a performance gap. *Total Quality Management*, 3 (2), 177–188.

Zhu, Q., Bai, C., & Sarkis, J. (2022). Blockchain technology and supply chains: The paradox of the atheoretical research discourse. *Transportation Research Part E: Logistics and Transportation Review*, 164, 102824.